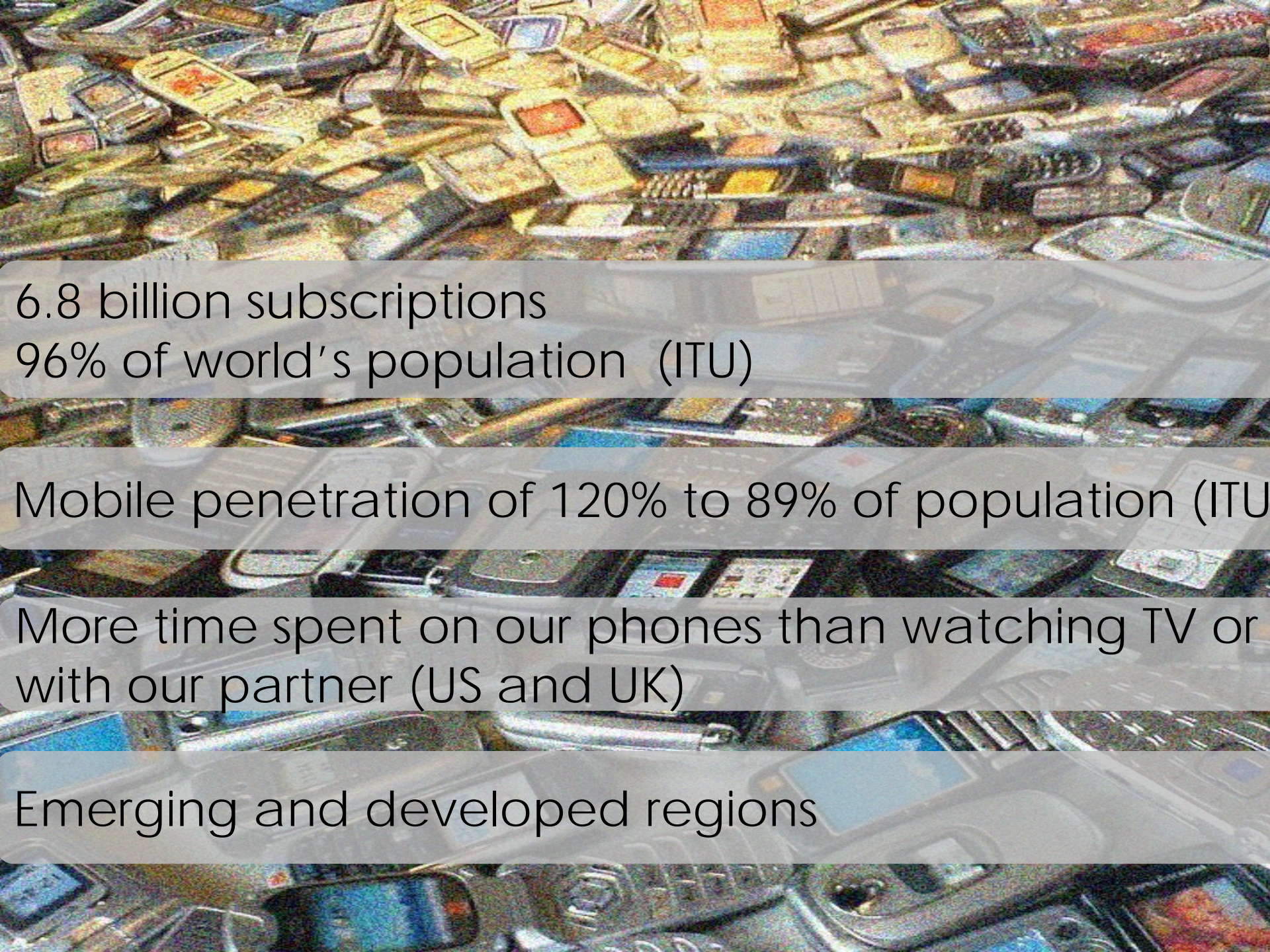




# SENSING THE CITY: URBAN ANALYSIS FOR THE XXI CENTURY

enrique.friasmartinez AT Telefonica.com

www.enriquefrias-martinez.info



6.8 billion subscriptions  
96% of world's population (ITU)

Mobile penetration of 120% to 89% of population (ITU)

More time spent on our phones than watching TV or  
with our partner (US and UK)

Emerging and developed regions

# Cell Phones as Sensors of Human Activity

Digital footprints enable large-scale analysis of human behavior

## Bits

Business ■ Innovation ■ Technology ■ Society

May 19, 2011, 7:06 pm **The Sensors Are Coming!**

By [NICK BILTON](#)

[Telecom](#) / [Wireless](#)

NEWS

**Cellphones for Science**

**Scientists want to put sensors into everyone's hands**

ieee  
spectrum  
INSIDE TECHNOLOGY

# Unprecedented Historic Moment

## Digital Footprints

For the first time in human history, we have access to large-scale human behavioral data at varying levels of spatial and temporal granularities

Collecting **large volumes of real data** about **human urban behavior** is a challenging yet high value problem



High-level Panel   
the Post-2015 Development Agenda

HOME

ABOUT

THE PANEL

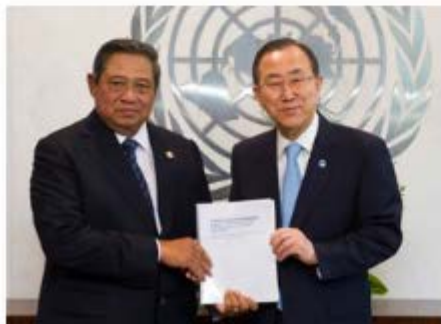
THE SECRETARIAT

OUTREACH

THE REPORT

MEDIA

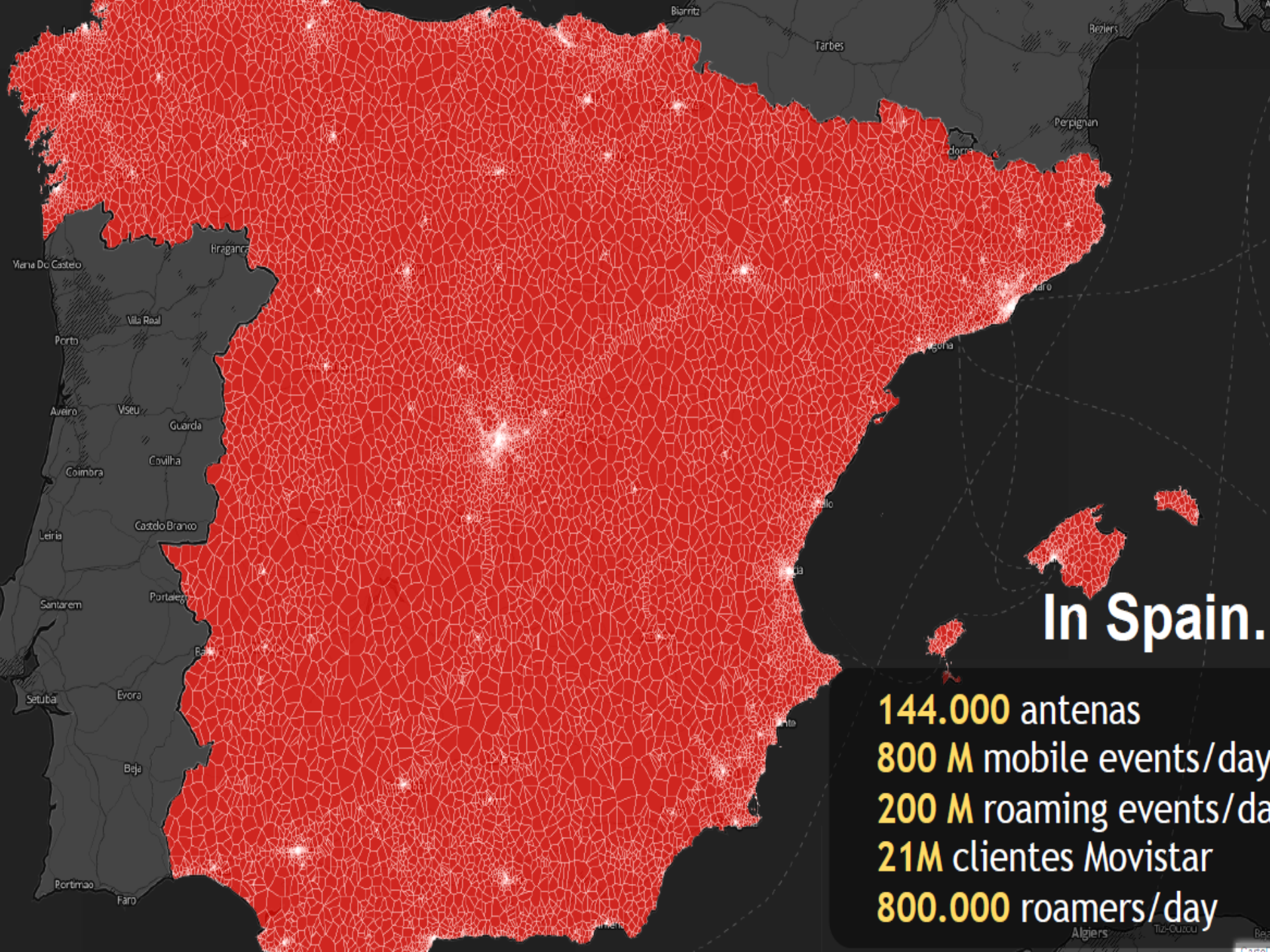
## HIGH LEVEL PANEL RELEASES RECOMMENDATIONS FOR WORLD'S NEXT DEVELOPMENT AGENDA



*Eminent Persons from Around the World Call for a New Global Partnership to Eradicate Poverty and Transform Economies through Sustainable Development*

The High Level Panel on the Post-2015 Development Agenda today released “**A New Global Partnership: Eradicate Poverty and Transform Economies through Sustainable Development**,” a report which sets out a universal agenda to eradicate extreme poverty from the face of the earth by 2030, and deliver on the promise of sustainable development. The report calls upon the world to rally around a new Global Partnership that offers hope and a role to every person in the world.

# Wanted: A data revolution



**In Spain.**

**144.000** antenas  
**800 M** mobile events/day  
**200 M** roaming events/day  
**21M** clientes Movistar  
**800.000** roamers/day



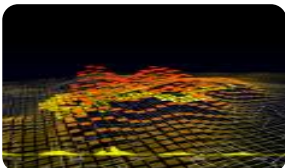
# Typical Mobile Data

- CDR

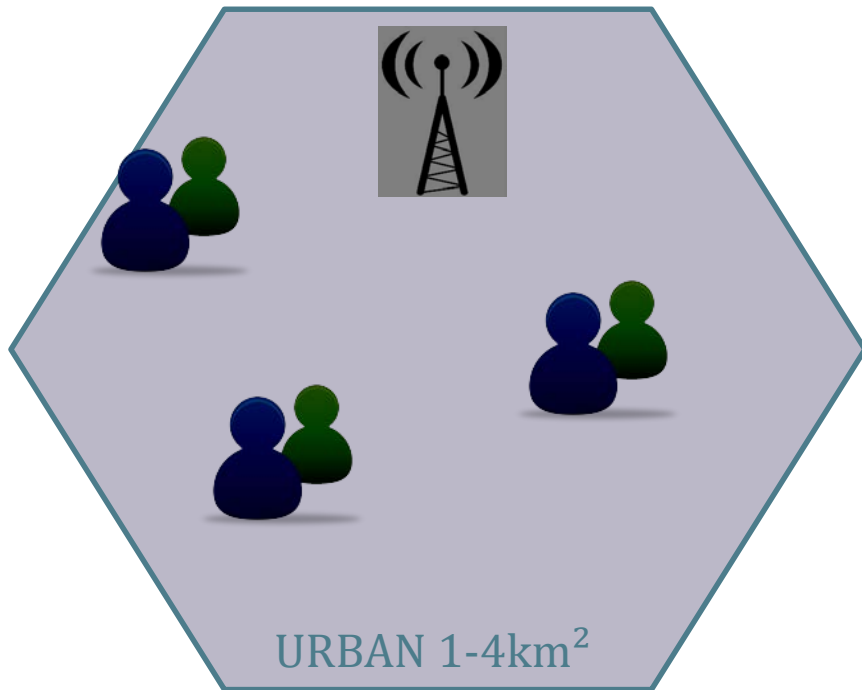
HR_ORG	TLFN_A	TLFN_B	CD_GEO_A	CD_GEO_B	DT_ORG	CD_SNTD	CD_ERB	CD_CCC	QT_DUR
20:05:31	XXX	YYY	3	11	20140519	2	1562	568	33
...	...	...	...	...	...	...	...	...	...

- SMS

HR_ORG	TLFN_A	TLFN_B	CD_GEO_A	CD_GEO_B	DT_ORG	CD_SNTD	QT_TRFG
15:53:54	XXX	ZZZ	3	25	20140506	2	1
...	...	...	...	...	...	...	...

Consumption	Social Network	Mobility
Call duration	In/Out Degree	Radius of gyration
N. Events	Delta w.r.t time window	Travelled distance
Lapse between events	Unique Calls per day	Rate of popular antennas
Reciprocated events	Unique SMS per day	Regularity of popular
		

# Call Detail Records





flickr™



facebook.

rsquare



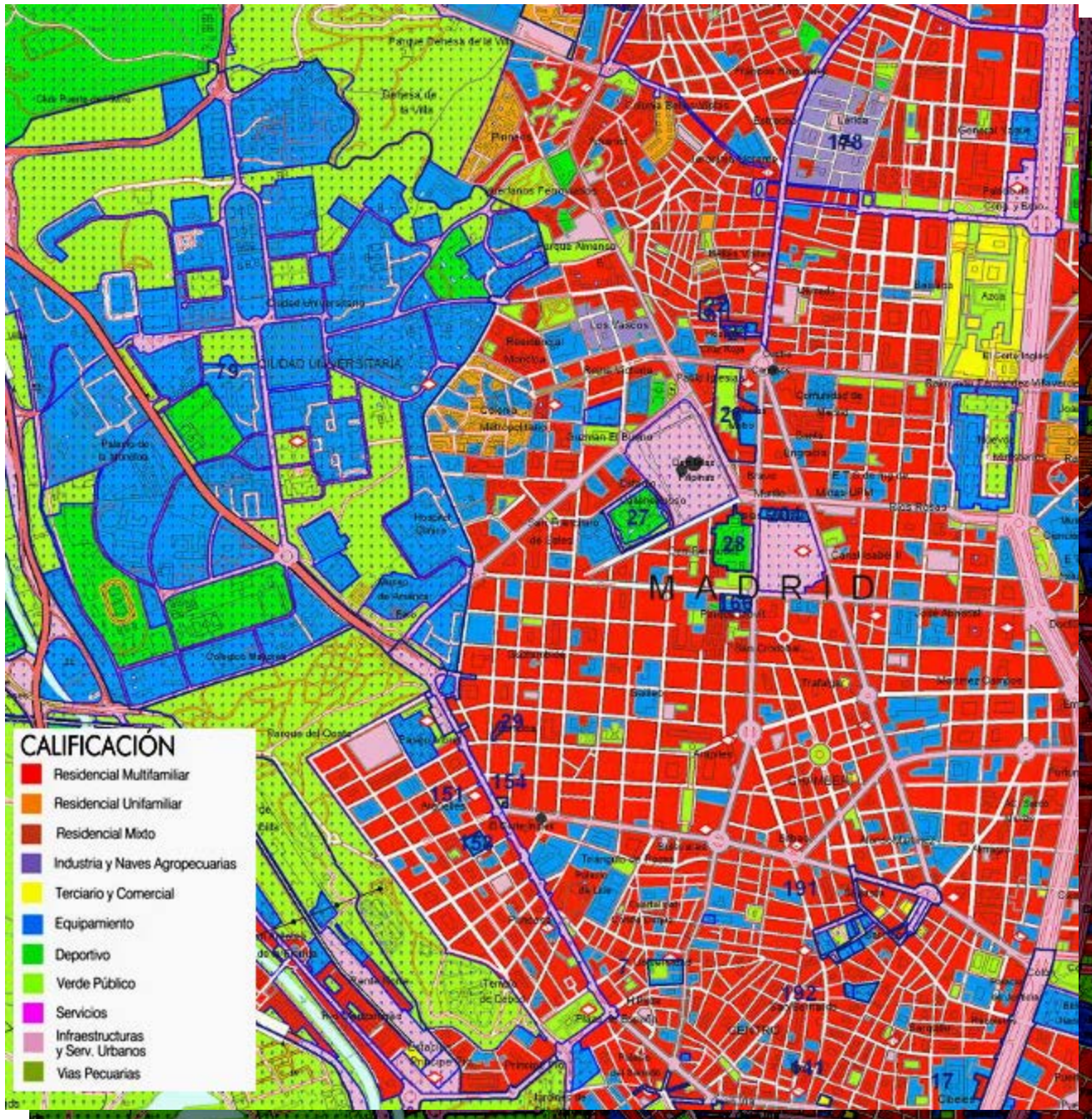
Paying for parking is now quicker and easier with

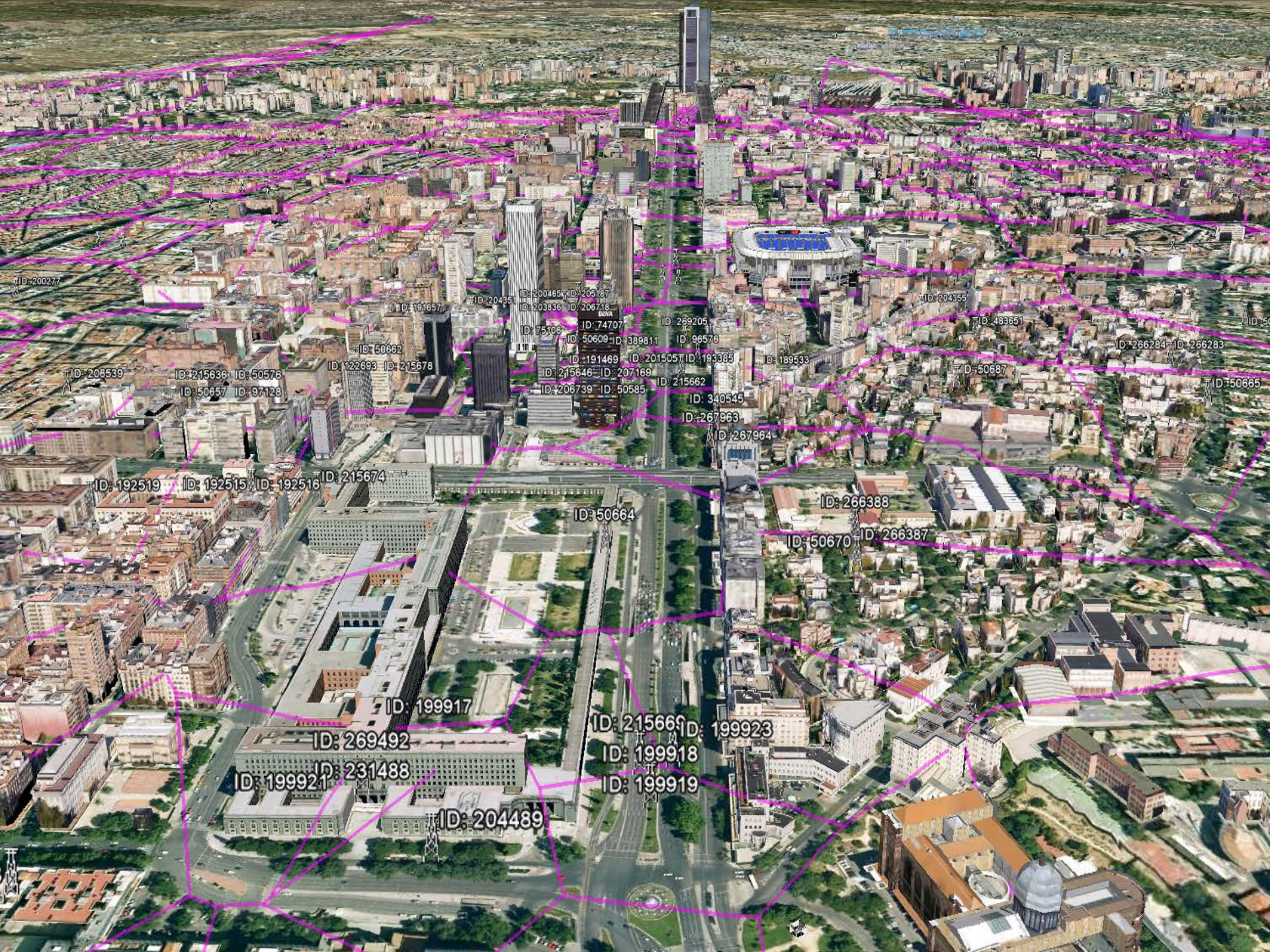
**E-ZPass Plus**

The fast, convenient way to pay for parking!

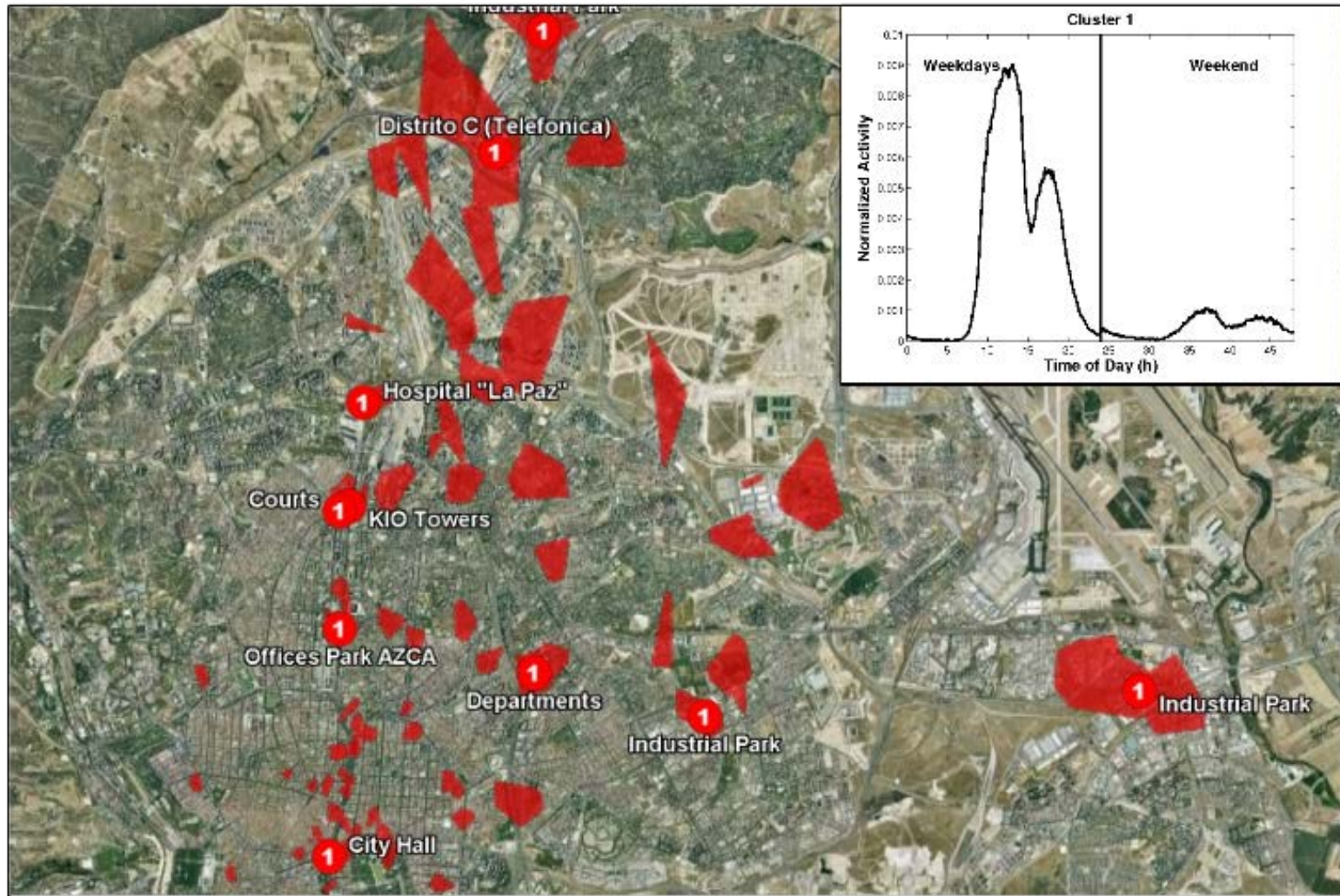
E-ZPass Plus is the new payment method that lets E-ZPass pay for parking.



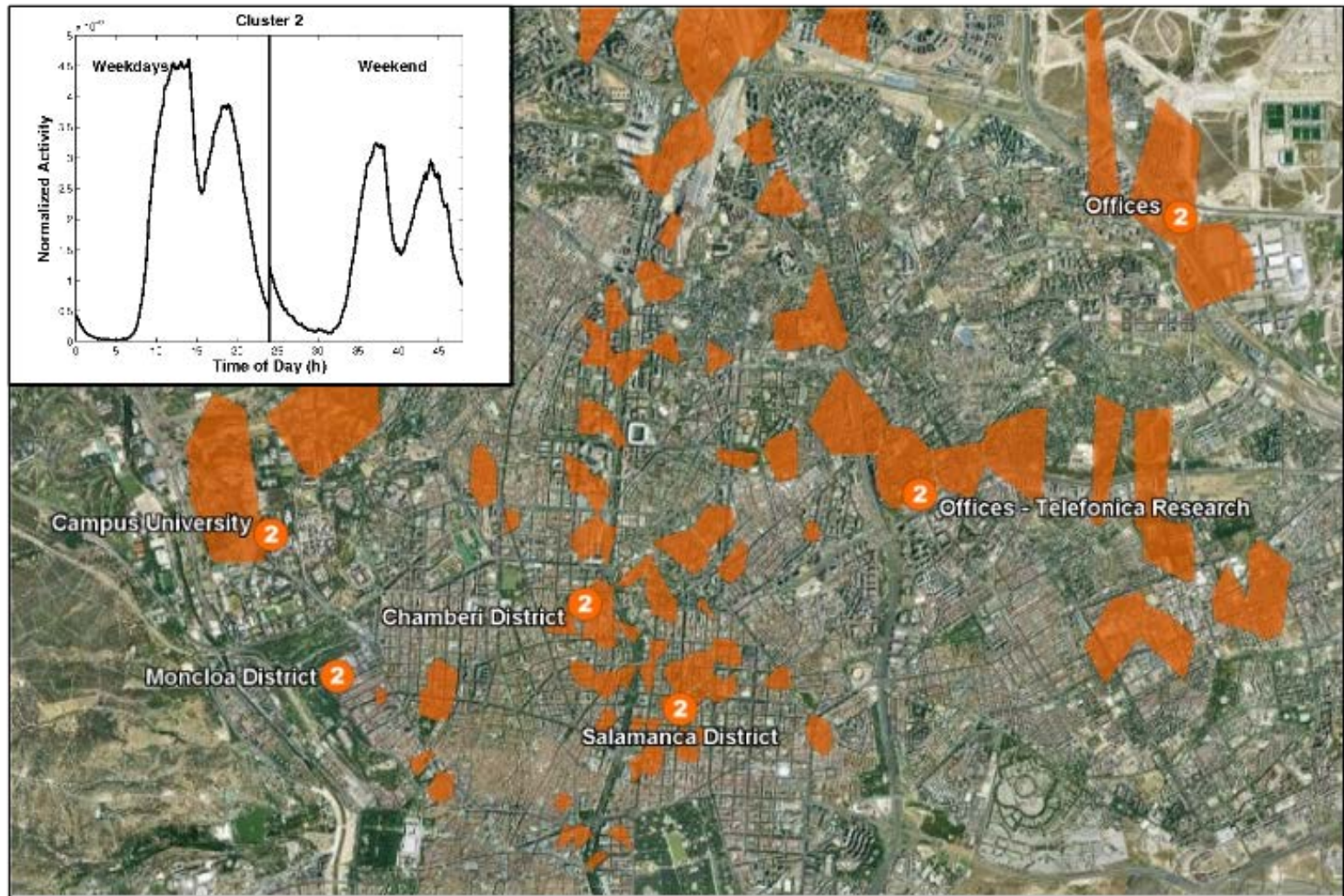




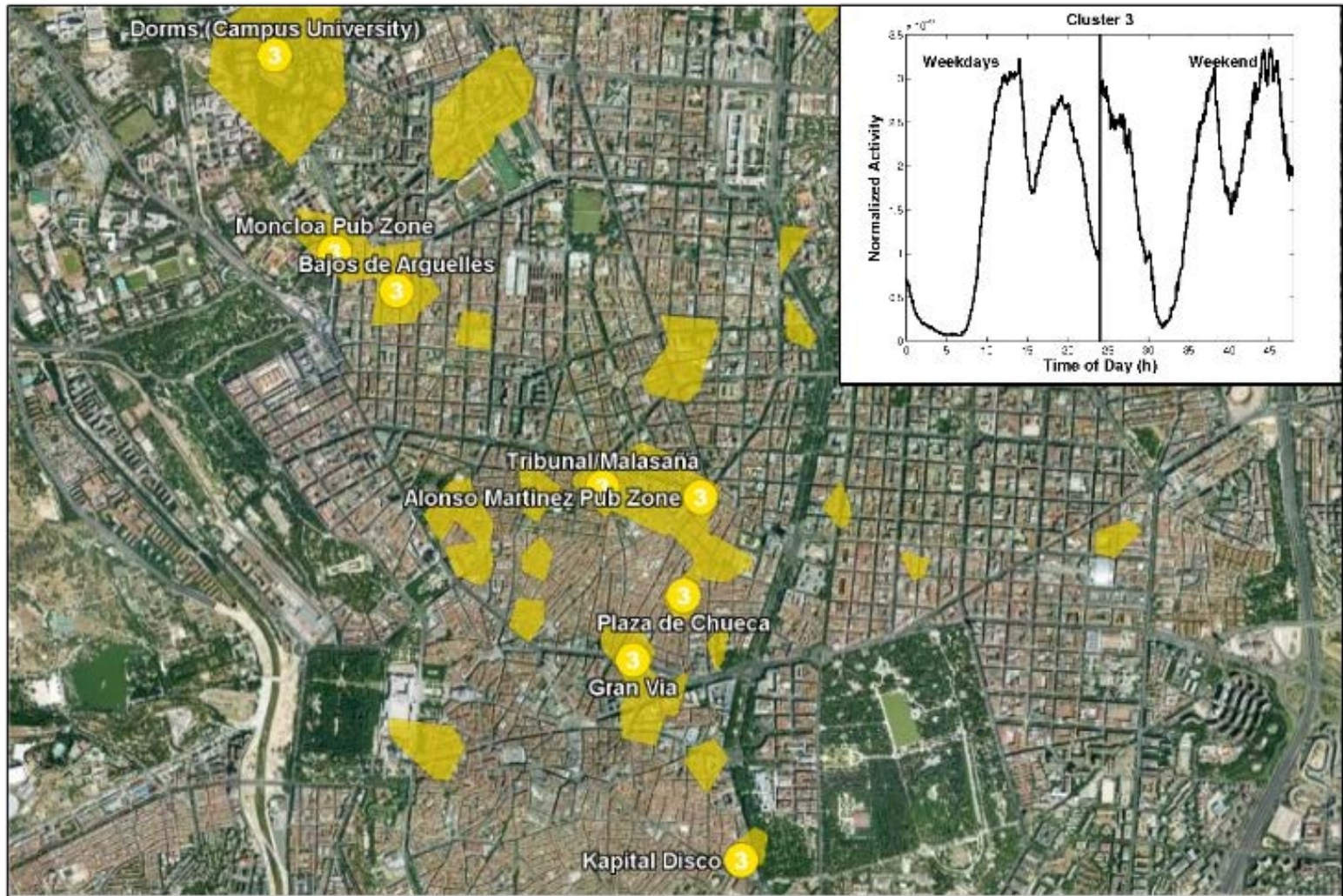
# Cluster 1: Industrial & Office



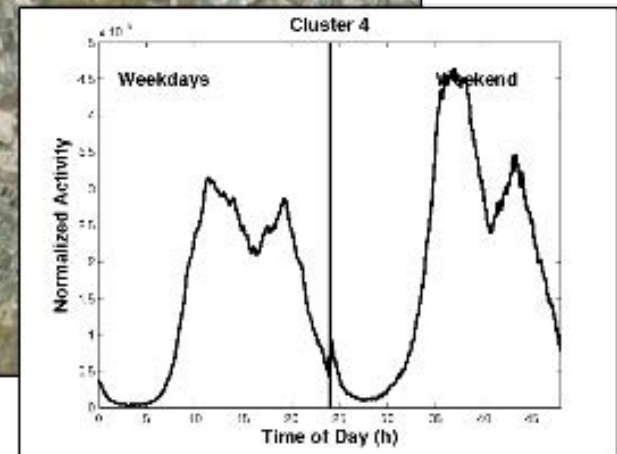
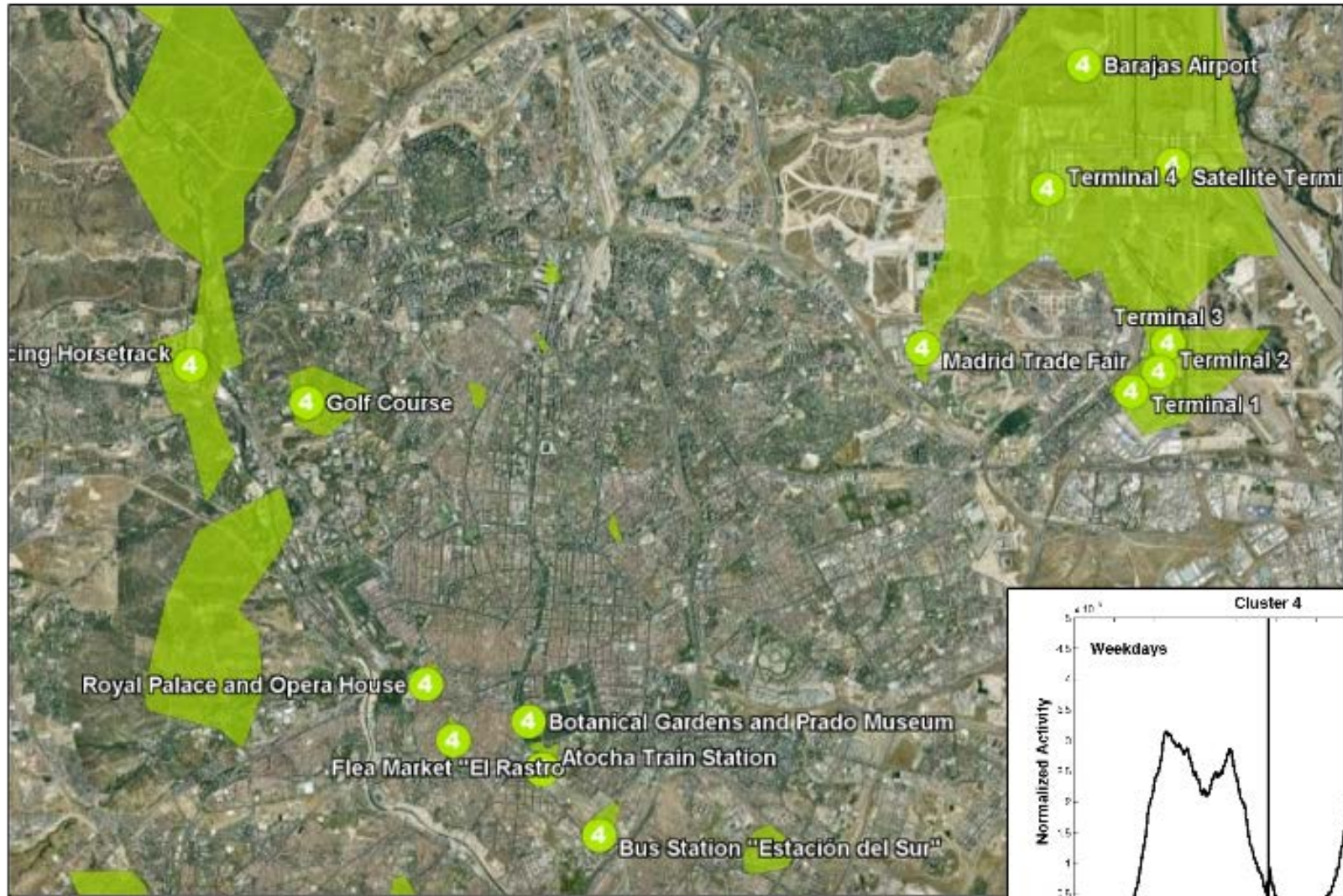
# Cluster 2: Business & Commercial



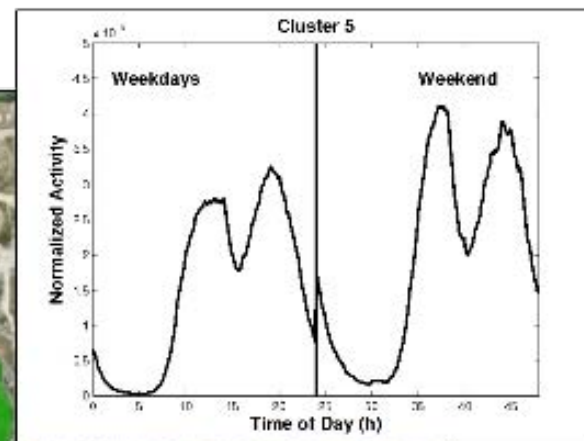
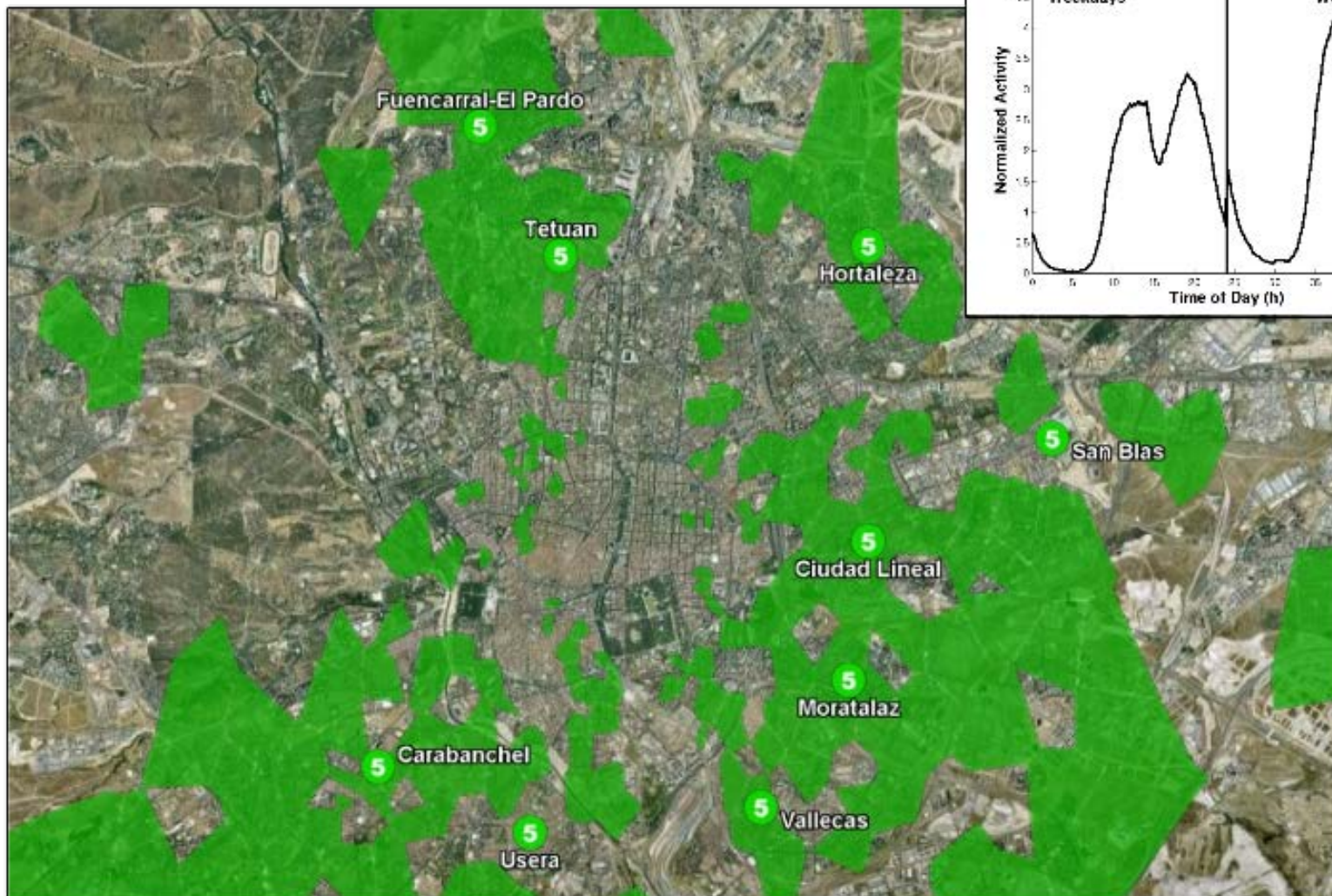
# Cluster 3: Nightlife



# Cluster 4: Leisure & Transport



# Cluster 5: Residential



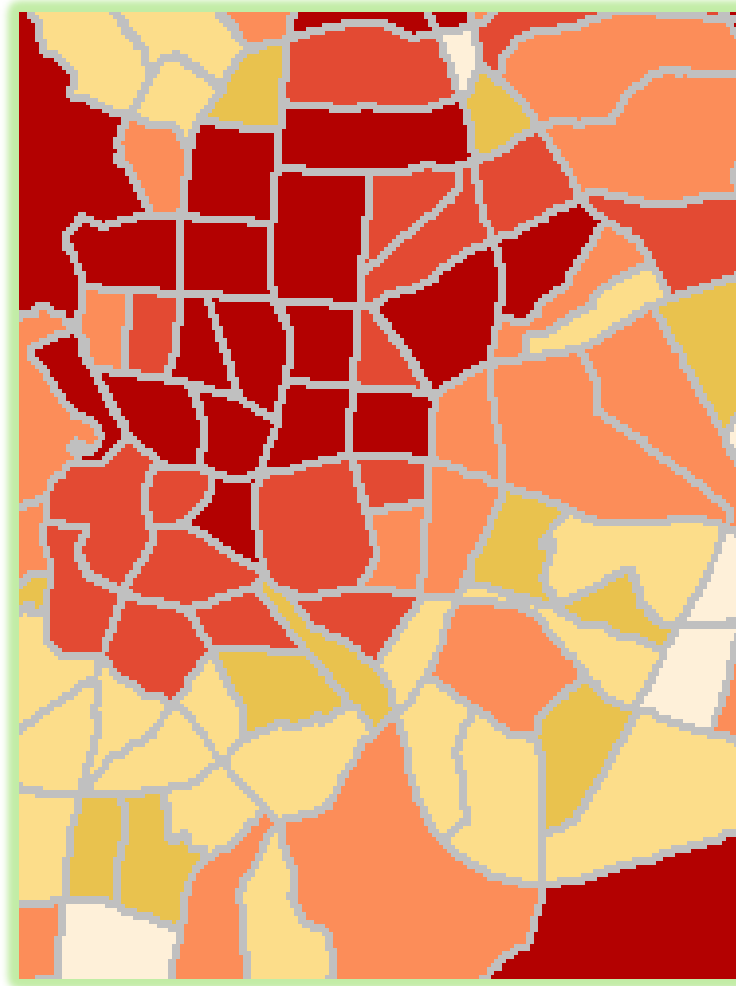
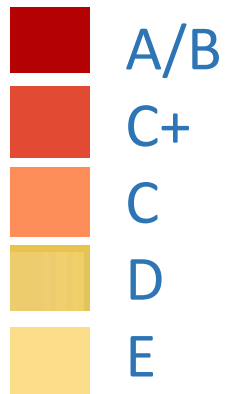




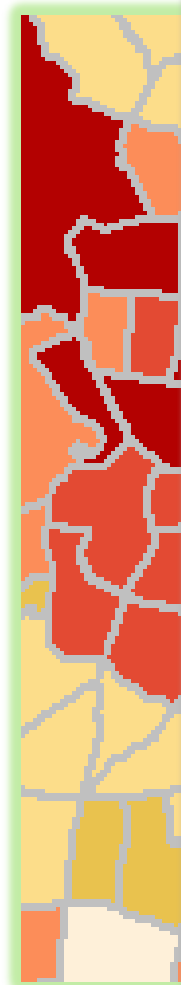
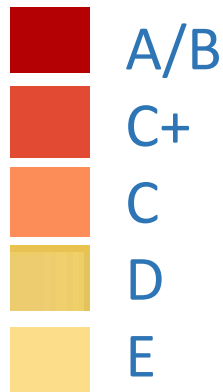
# Socioeconomic Maps

Computing Socioeconomic Maps  
from Cell Phone Data

# Motivation: Socioeconomic Maps

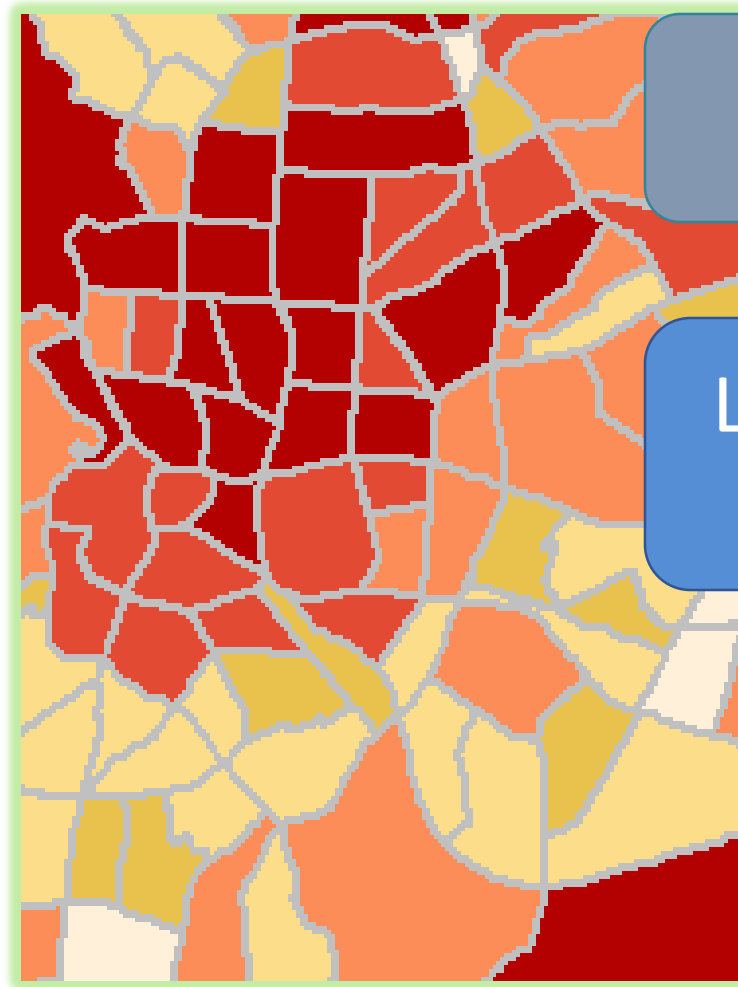
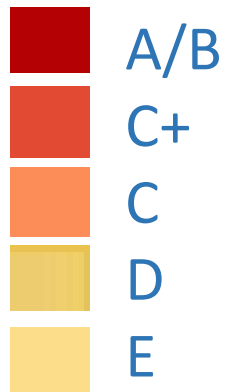


# National Statistical Institutes (NSI)



Census Variables	
Variable Type	Description
Education	% of Population with Primary School
	% of Female Population with Primary School
	% of Male Population with Primary School
	% of Population with Secondary School
	% of Female Population with Secondary School
	% of Male Population with Secondary School
	% of Illiterate Population
	% of Female Illiterate Population
	% of Male Illiterate Population
Demographics	% of Female Population
	% of Male Population
	% of Young Population (< 16)
	% of Middle-Age Population (16 – 60)
Goods	% of Senior Population (> 60)
	% of Houses with Cement Floor
	% of Houses with 1 room
	% of Houses with 3+ rooms
	% of Houses with Electricity
	% of Houses with Water
	% of Houses with TV
	% of Houses with PC
% of Houses with All	
SEL	Socio-Economic Level

# Important Data Comes at a Price



Expensive

Low resource regions

Can human behaviors extracted from Call Detail Records be used to forecast regional socioeconomic information?

# Modeling Human Behavior



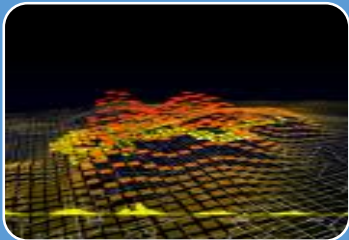
## Consumption

- Number calls, duration, frequency, SMS/MMS/voice
- Expenses
- Handset Type and Features



## Social

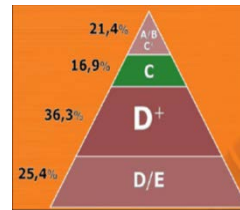
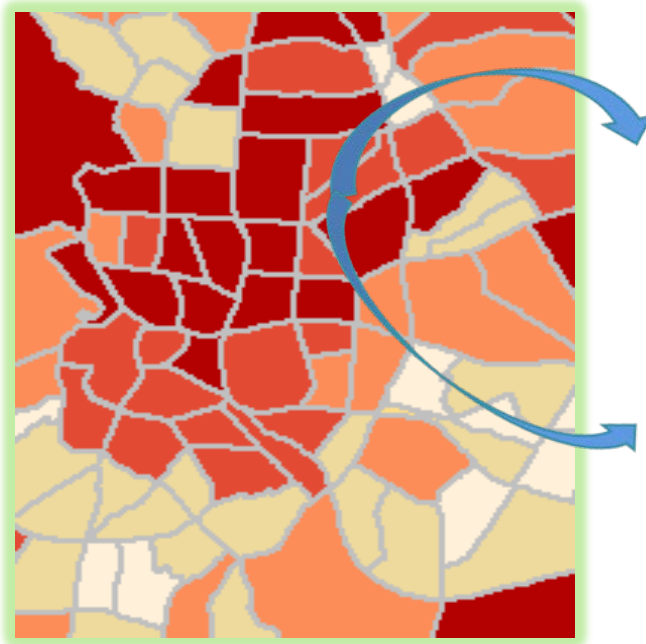
- Degree of the social network
- Strength of the contacts (Reciprocity & Frequency)
- Geography of the social contacts



## Mobility

- Mobility Patterns (Entropy)
- Diameter of mobility
- Radius of gyration (Home/Work)

# Methodology



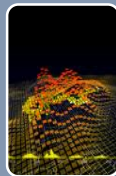
**SEL (NSI)**



**Consumption**



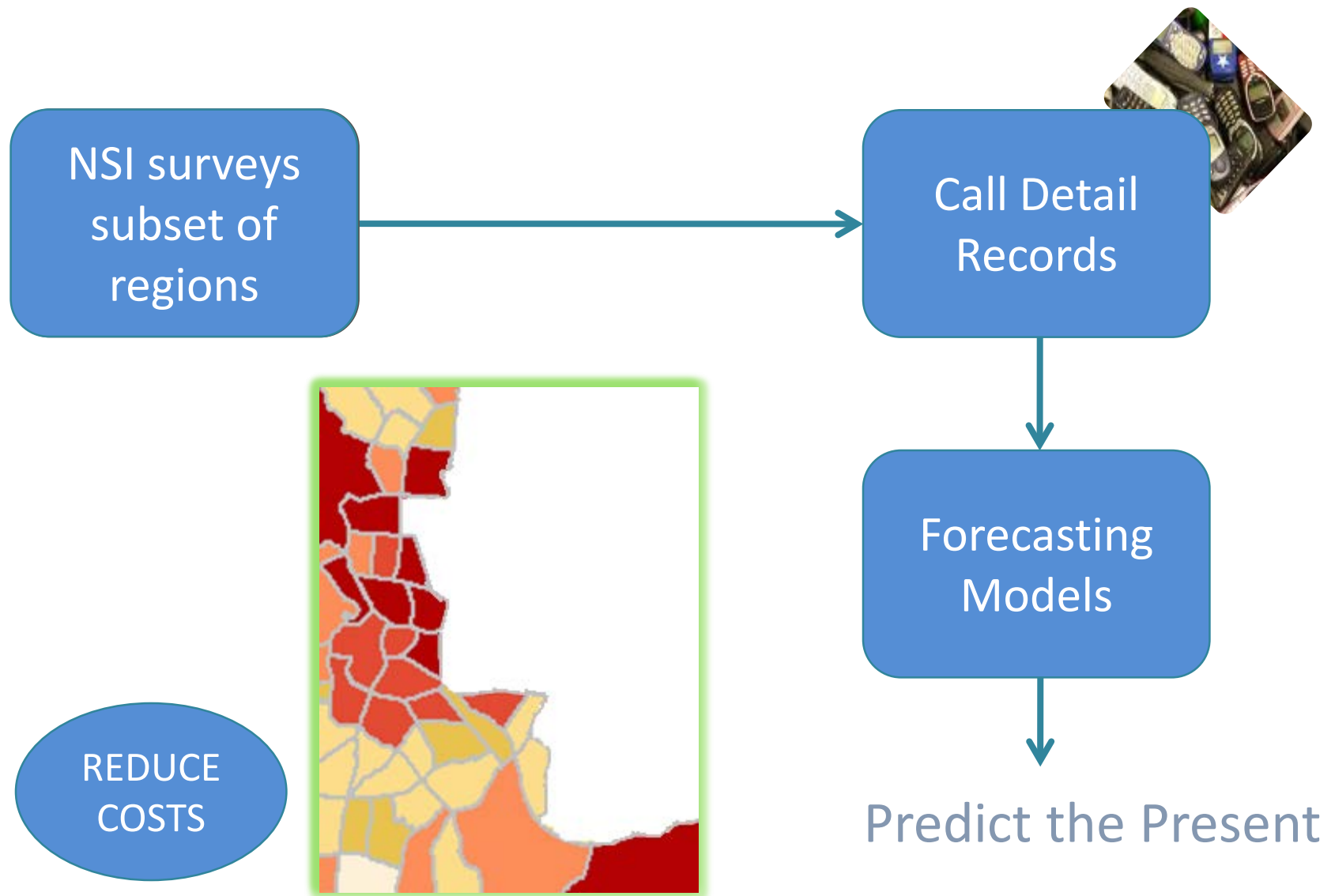
**Social**



**Mobility**

**CLASSIFIER**

# Cost-effective Maps





# Datasets

- Data for a city in Latin America (NSI)
  - 1200 regions (GUs)
  - SEL values from 0..100
- Call Detail Records
  - 6 months, 500K customers
  - City has 920 coverage areas
  - 279 variables per coverage area

# Evaluation Results (6 SELs)

**EM Clustering**

**P=62%**

20 features , 6 classes

**Random Forests**

**P=60%**

22 features

**SVM**

**P=57%**




19 features

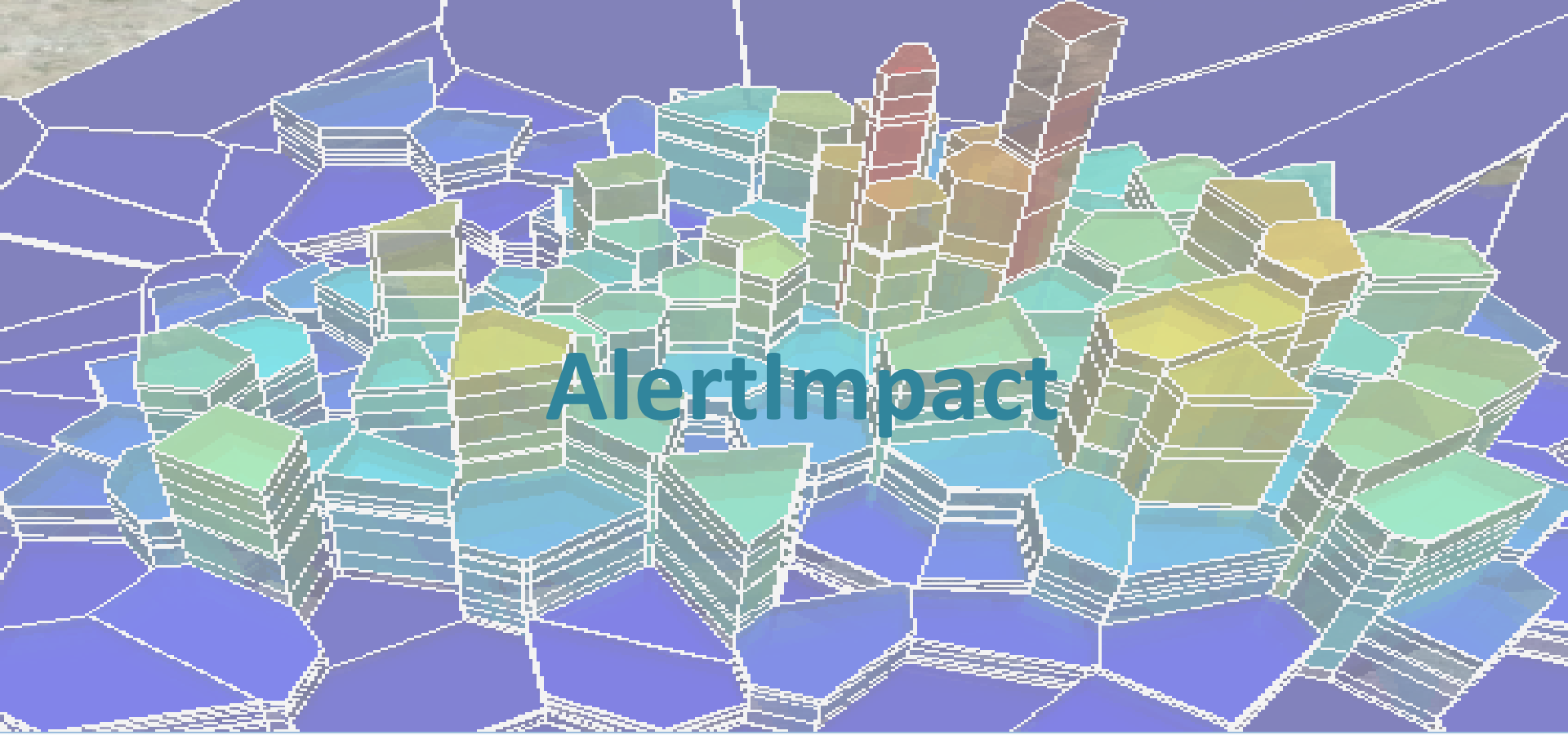
## CLASSIFICATION

	A	B	C	D	E	F
A	<b>0.59</b>	0.41	0.00	0.00	0.00	0.00
B	0.10	<b>0.60</b>	0.30	0.00	0.00	0.00
C	0.00	0.20	<b>0.66</b>	0.14	0.00	0.00
D	0.00	0.00	0.21	<b>0.64</b>	0.08	0.07
E	0.00	0.00	0.00	0.20	<b>0.60</b>	0.20
F	0.00	0.00	0.00	0.13	0.35	<b>0.52</b>

**Results superior to baseline**  
**No spatial autocorrelation**

# Most predictive features...

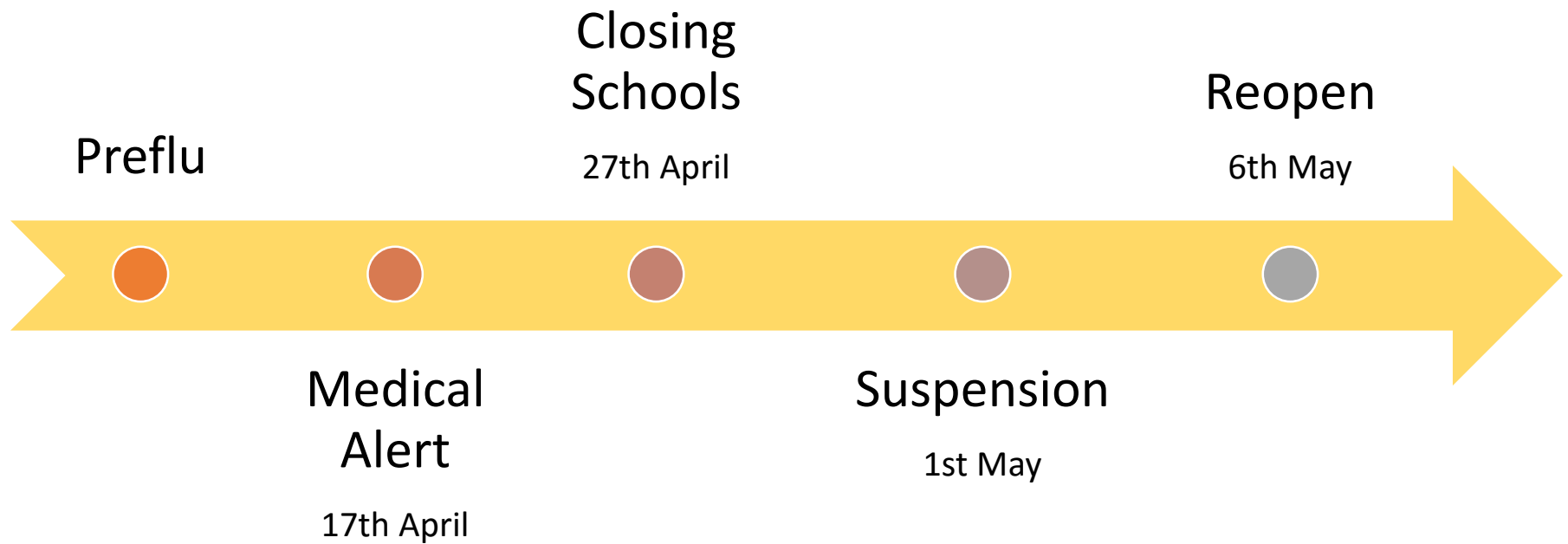
- Weekly average of different BTSs used 
- Percentage of incoming SMS over all communications 
- Percentage of SMS sent with high reciprocity 



**AlertImpact**

# Understanding the Impact of Health Alerts using Cell Phone Data

# H1N1 Mexico Timeline



Can we measure the effect that government alerts had on the mobility of the population using Call Detail Records?

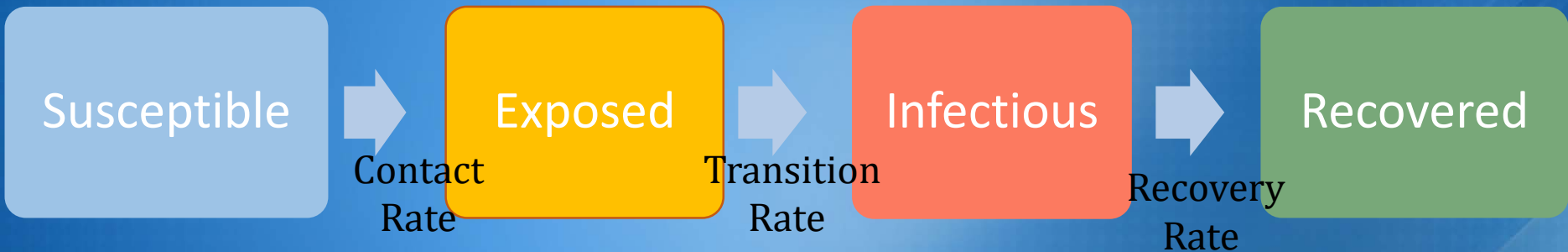
*(citizens do what they are asked to do)*

Can we measure the effect that government alerts had on the spreading of the epidemic using Call Detail Records?

*(government measures are useful)*

# Epidemic Disease Models

## ▣ Compartmental Models (SEIR)

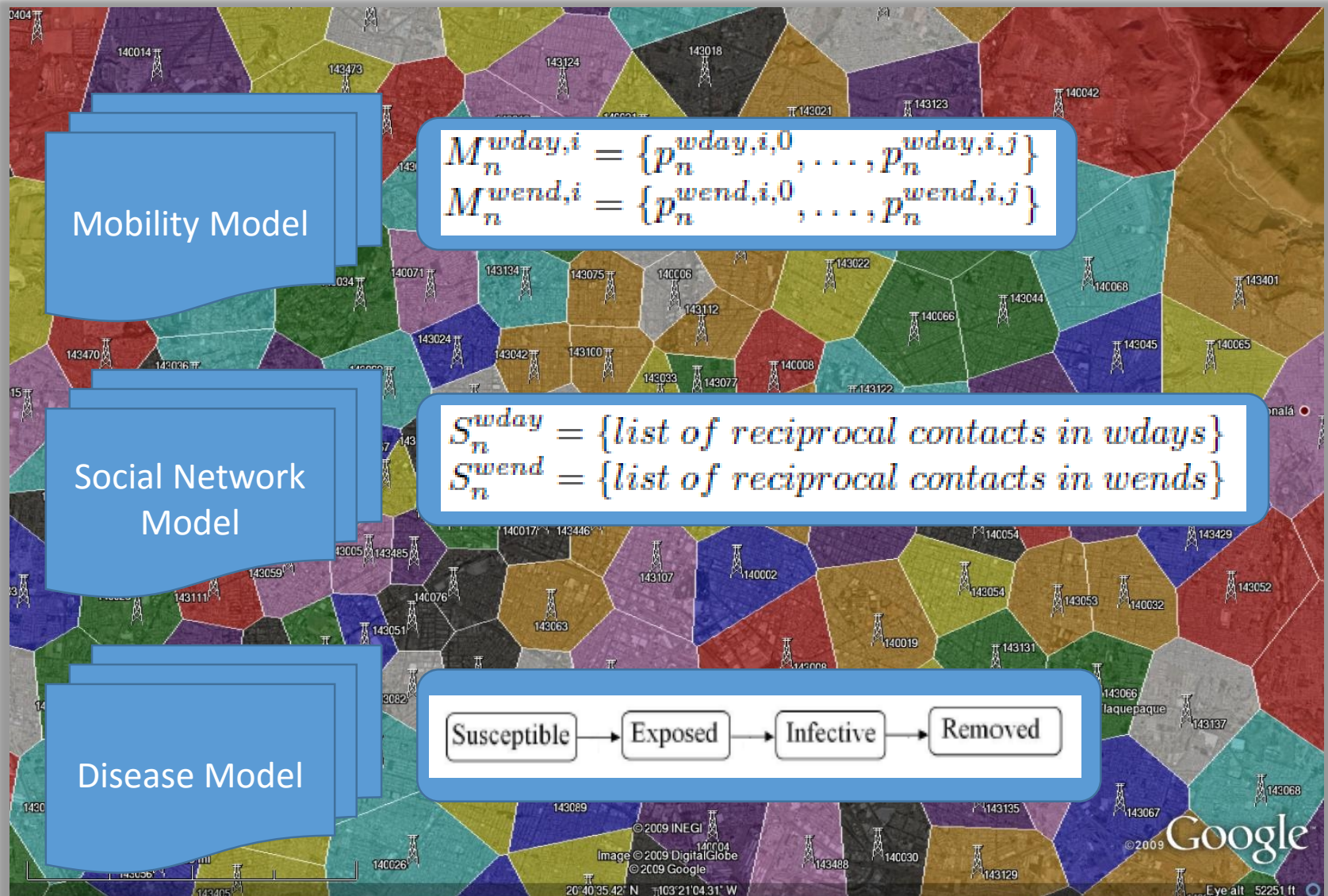


## ▣ Agent Based Models

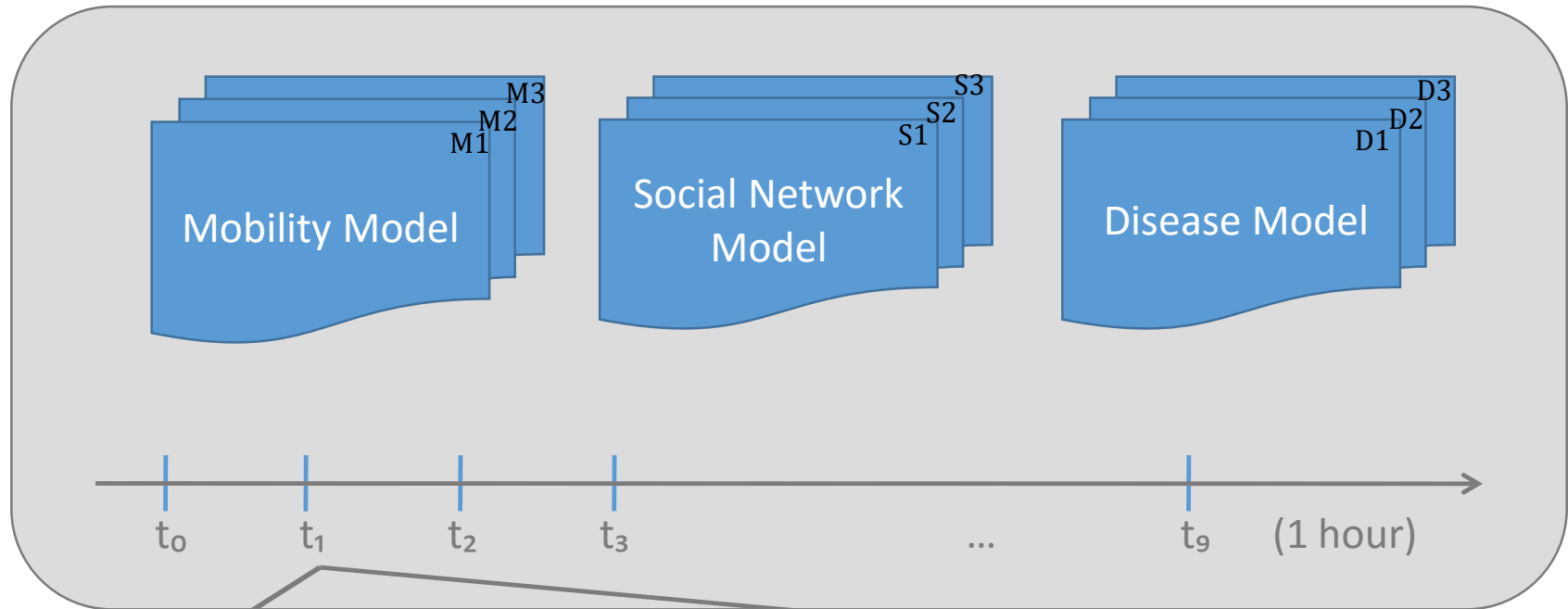
- Capture complexity of social interaction
- Limitation with the information available to generate the agents



# ABM for Virus Spreading using CDR

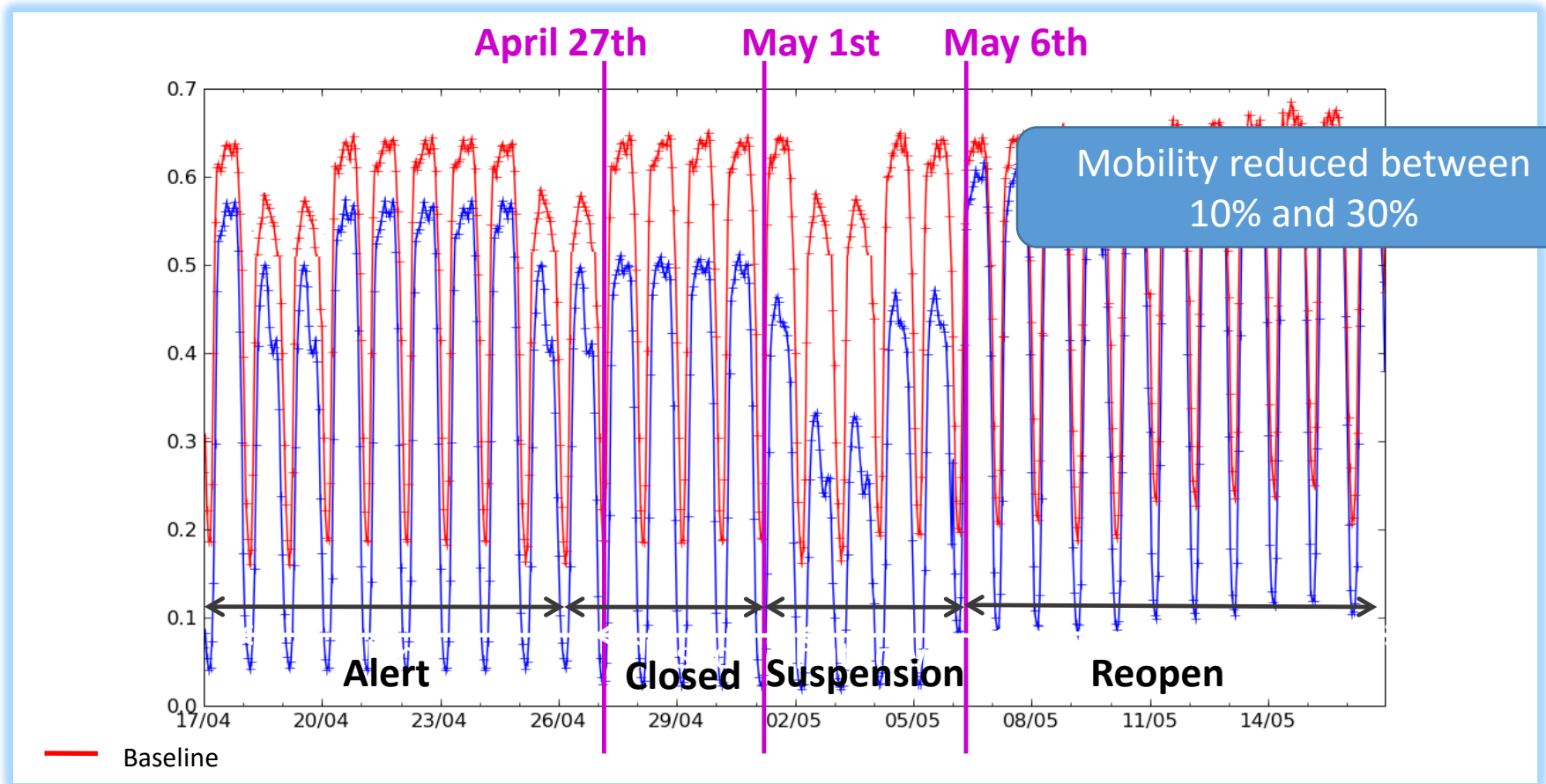


# Discrete Event Simulator

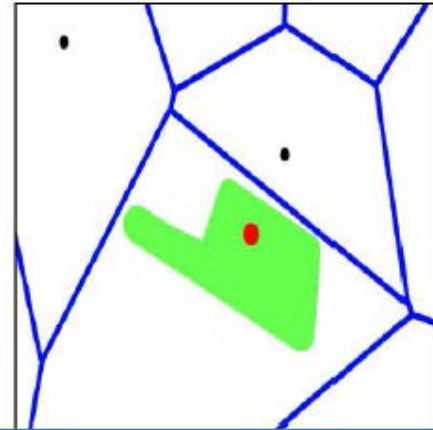


Identify geographical location (BTS)  
Identify peers in same BTS  
If peer in SN then evolve disease model with  $p_i$   
Else evolve disease model with  $p_j$

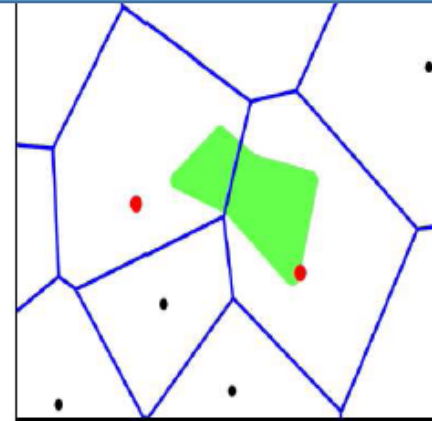
# Changes in Mobility



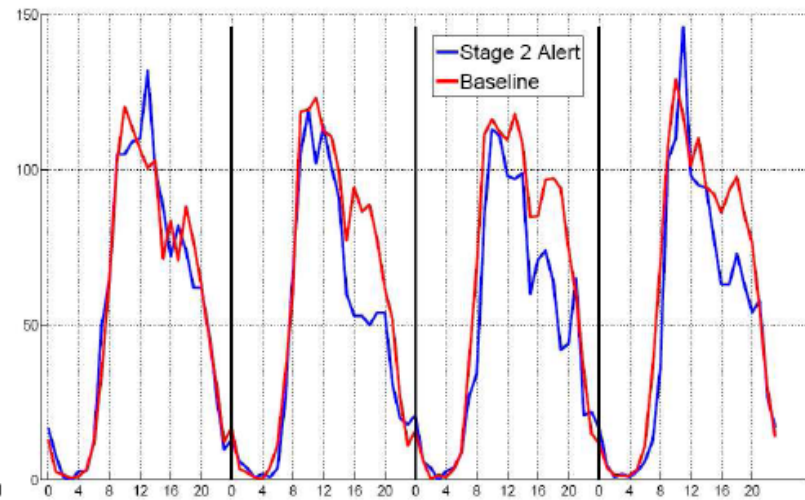
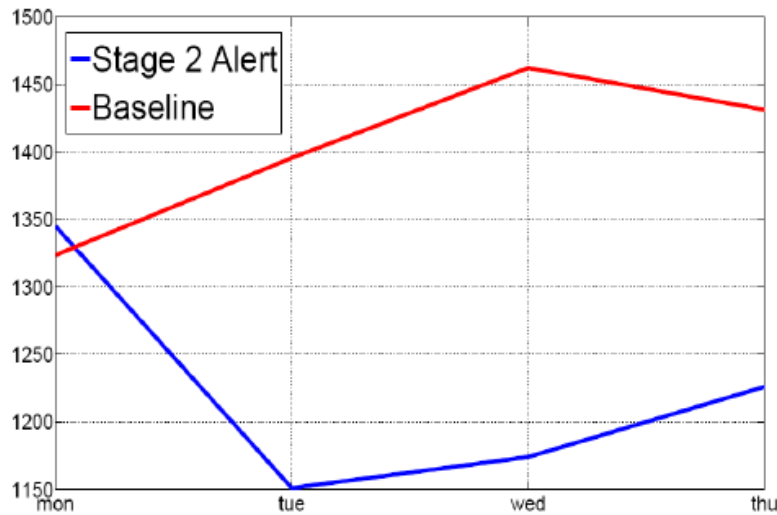
# Infrastructure Analysis



Only citizens that DO NOT LIVE in these BTS areas

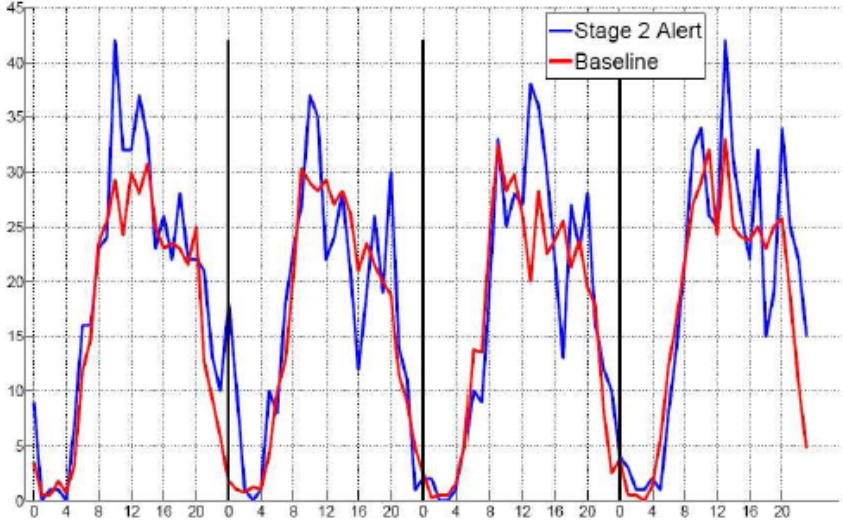
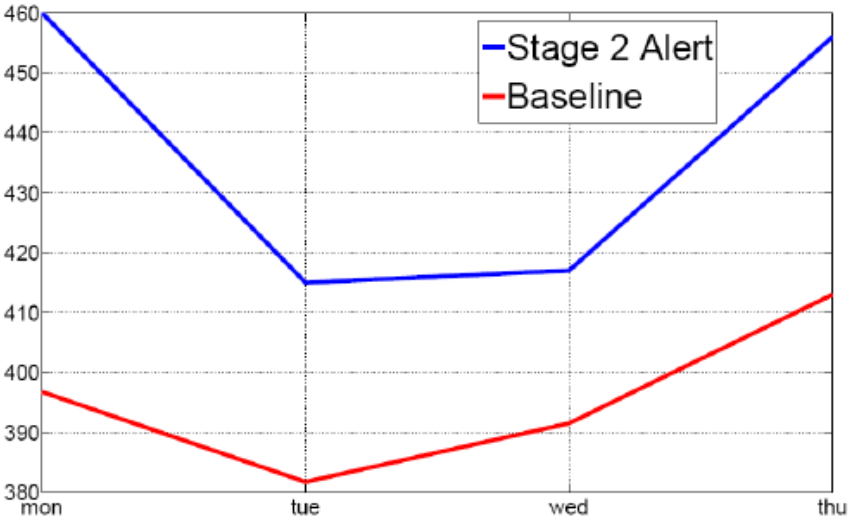


# University Campus



Statistically Significant  
Decrease during Stages 2 and 3

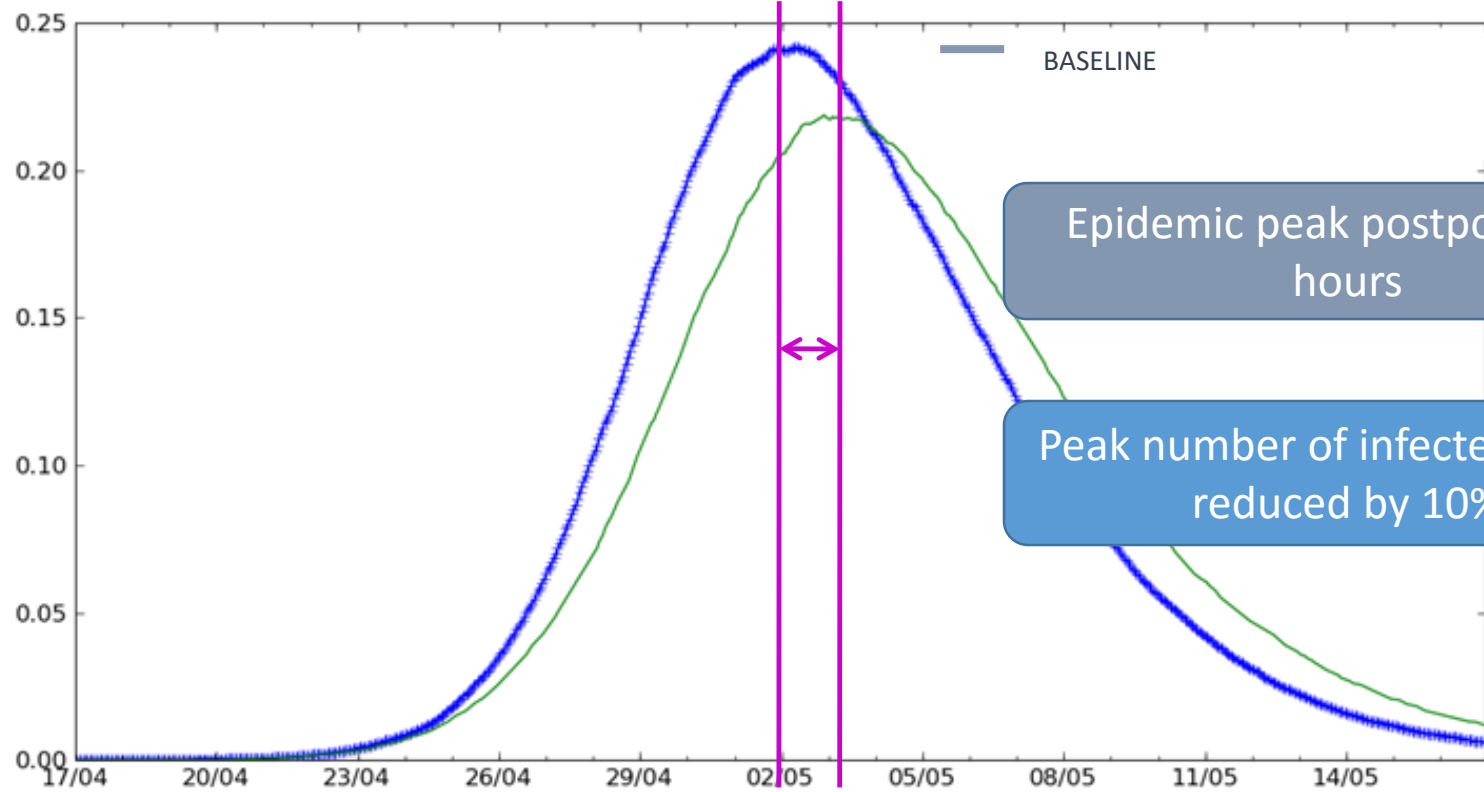
# Airport



Statistically Significant Increase during Stages 2 and 3

# Effect on Epidemic Spreading

# Evaluation



Epidemic peak postponed 40 hours

Peak number of infected agents reduced by 10%

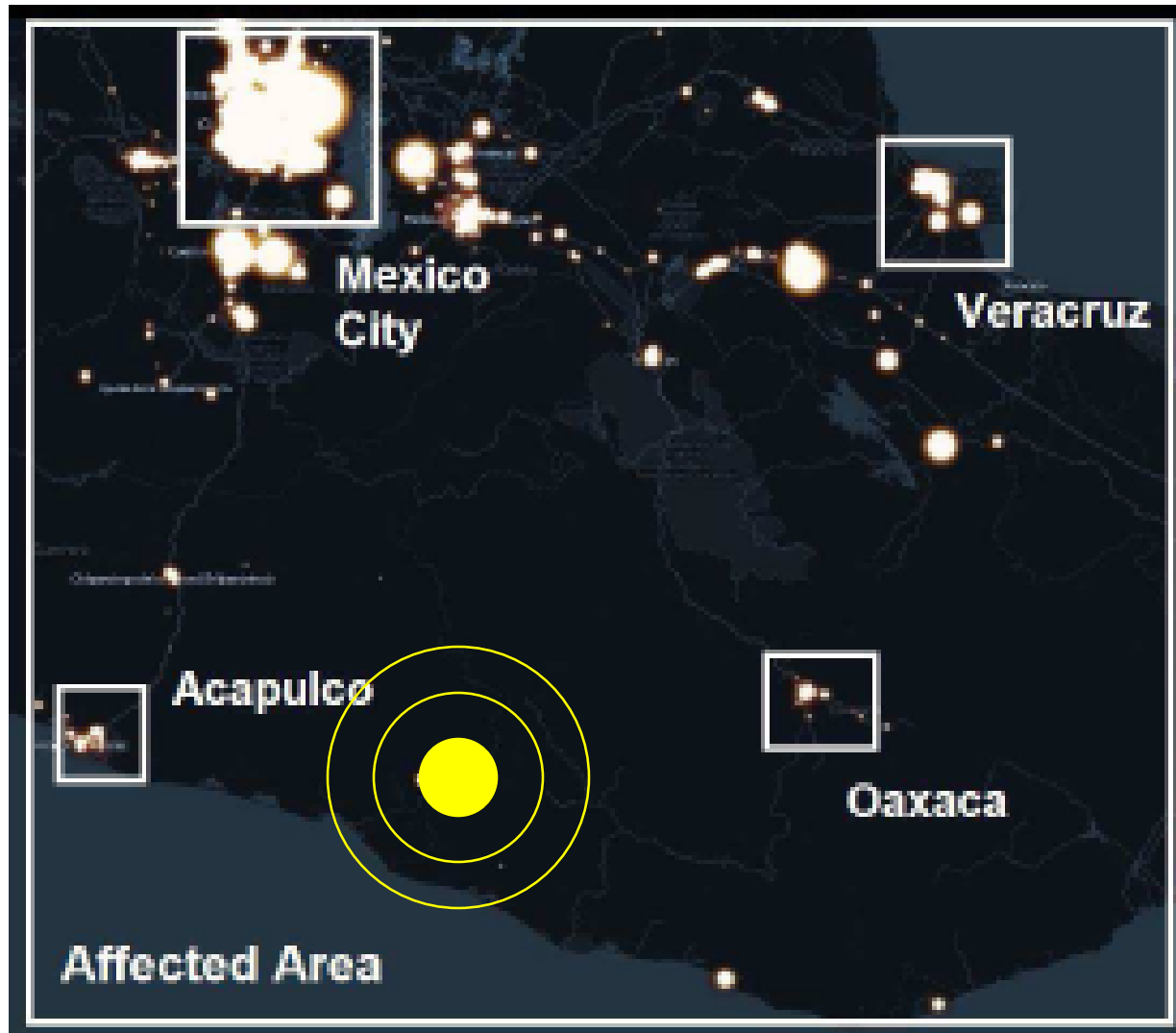




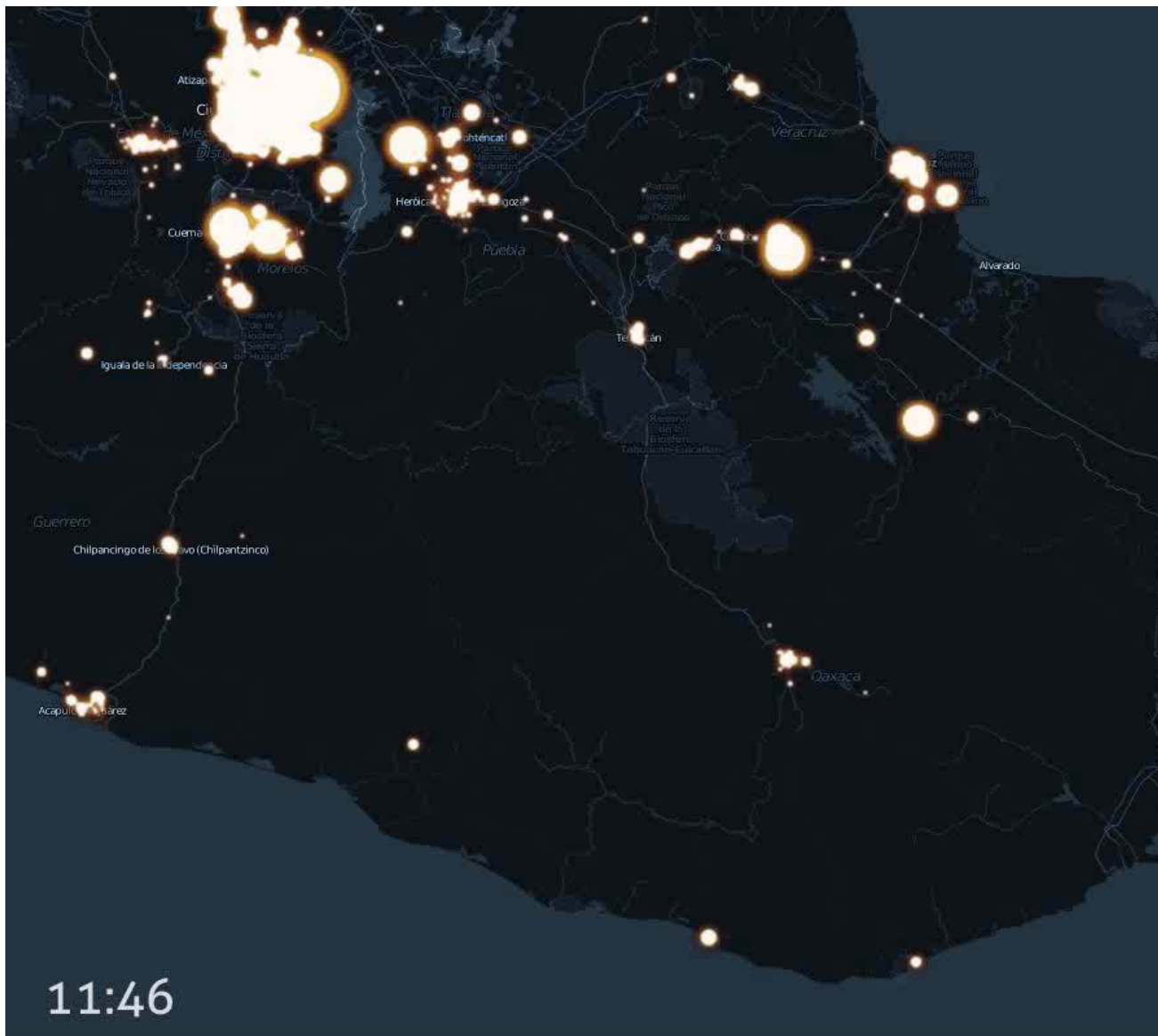
# Earthquakes

Characterizing the Social Response  
to an Earthquake

# Oaxaca Earthquake



Can we measure the social response to the earthquake using call detail records?



11:46

## Mexico 2012 Earthquake

Magnitude: 7.4

Date & Time: March 20, 2012 at 12:02:48 PM

Location: 16.662°N, 98.188°W

Depth: 20 km (12.4 miles)

Damage: 2 deaths

13 injuries

800 houses collapsed

Data: U.S. Geological Survey

Telefonica Mexico

OpenStreetMap



## Legend



Less activity

More activity



Earthquake



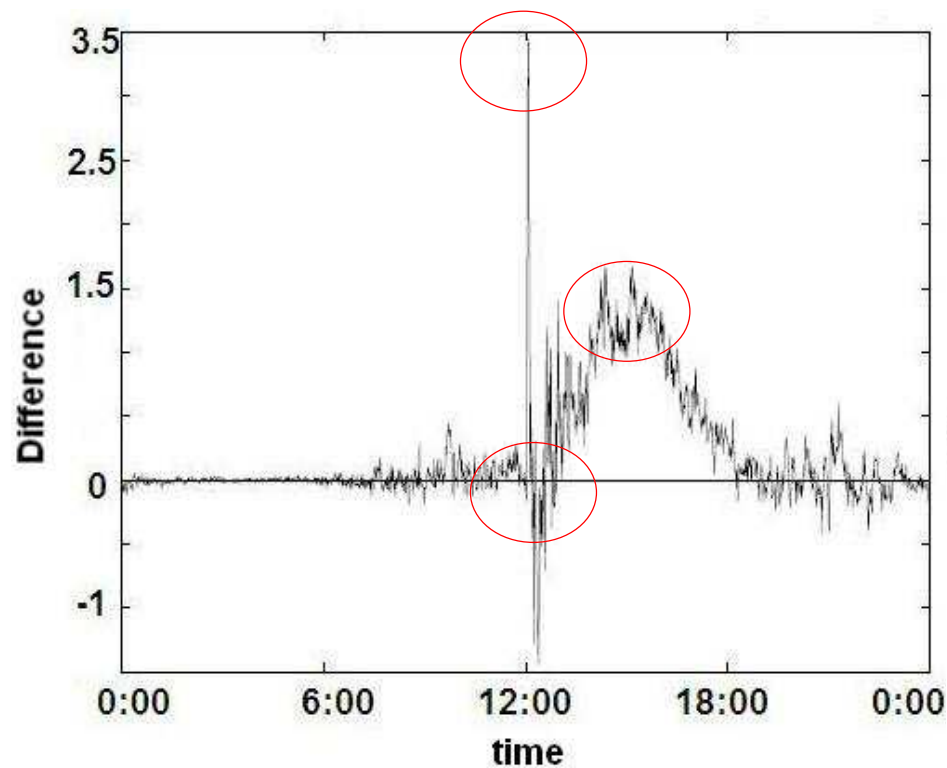
Aftershocks

# Methodology

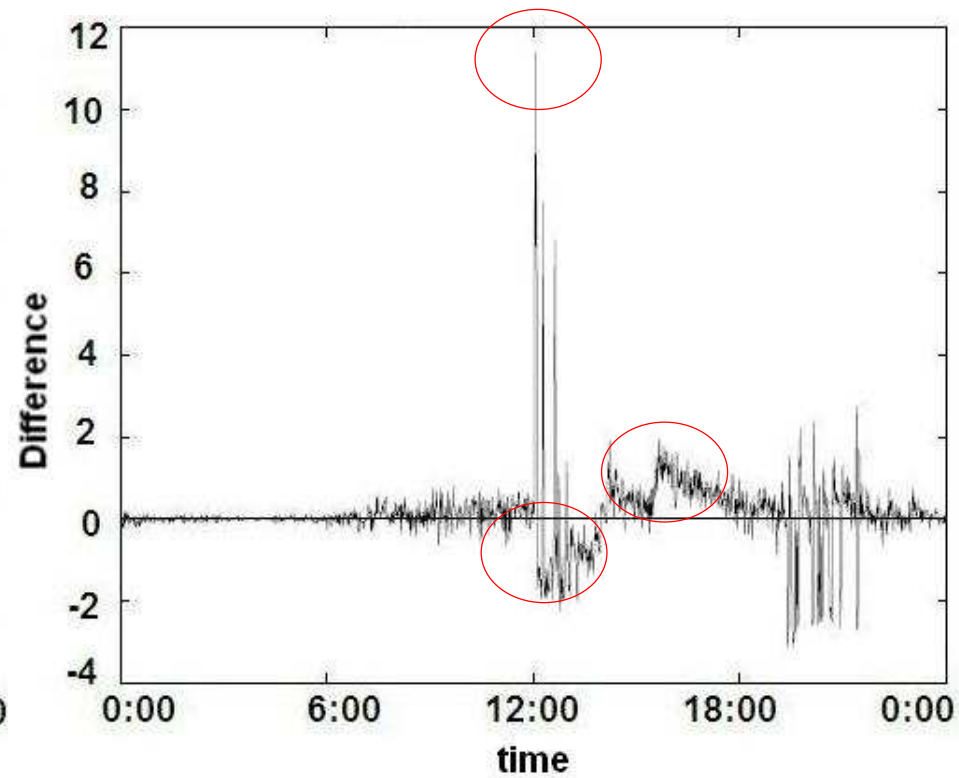
- Focus on three social responses:
  - Communication: call volumes and call durations
  - Social activity
  - Mobility
- Compare responses across cities
  - Day of the earthquake
  - Baseline

# Call Volumes

- Compute time series of call volumes with 1-minute resolution and compare to baseline (normalized difference)



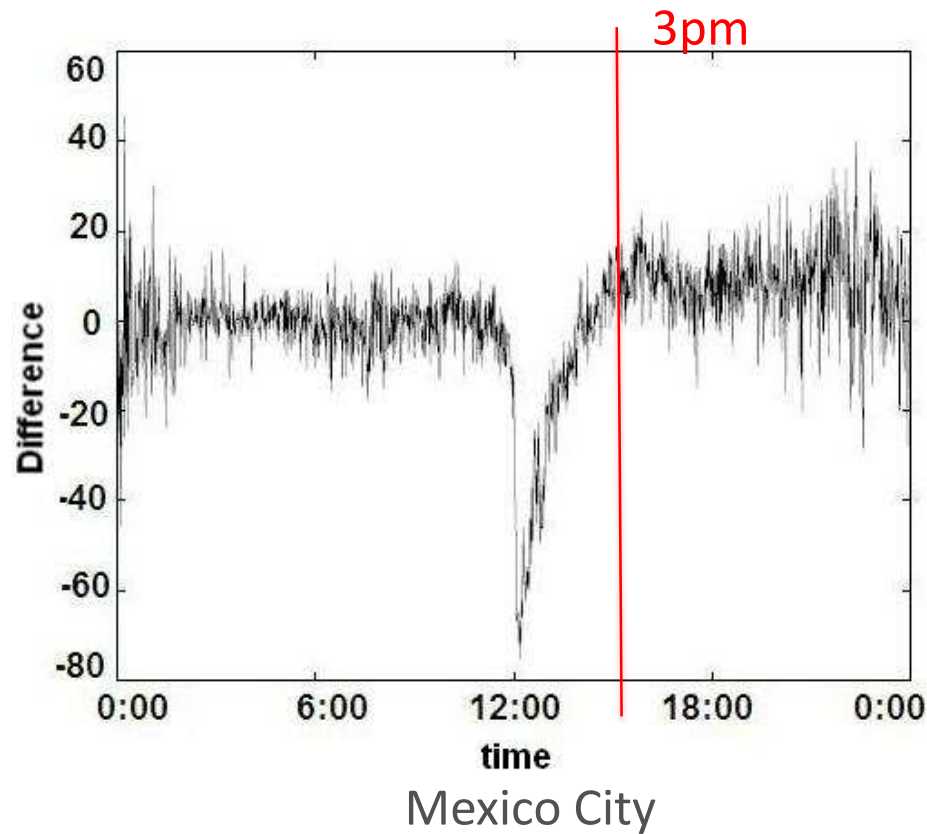
Mexico City



Oaxaca

# Call Duration

- Compute time series of call volumes with 1-minute resolution and compare to baseline (normalized difference)

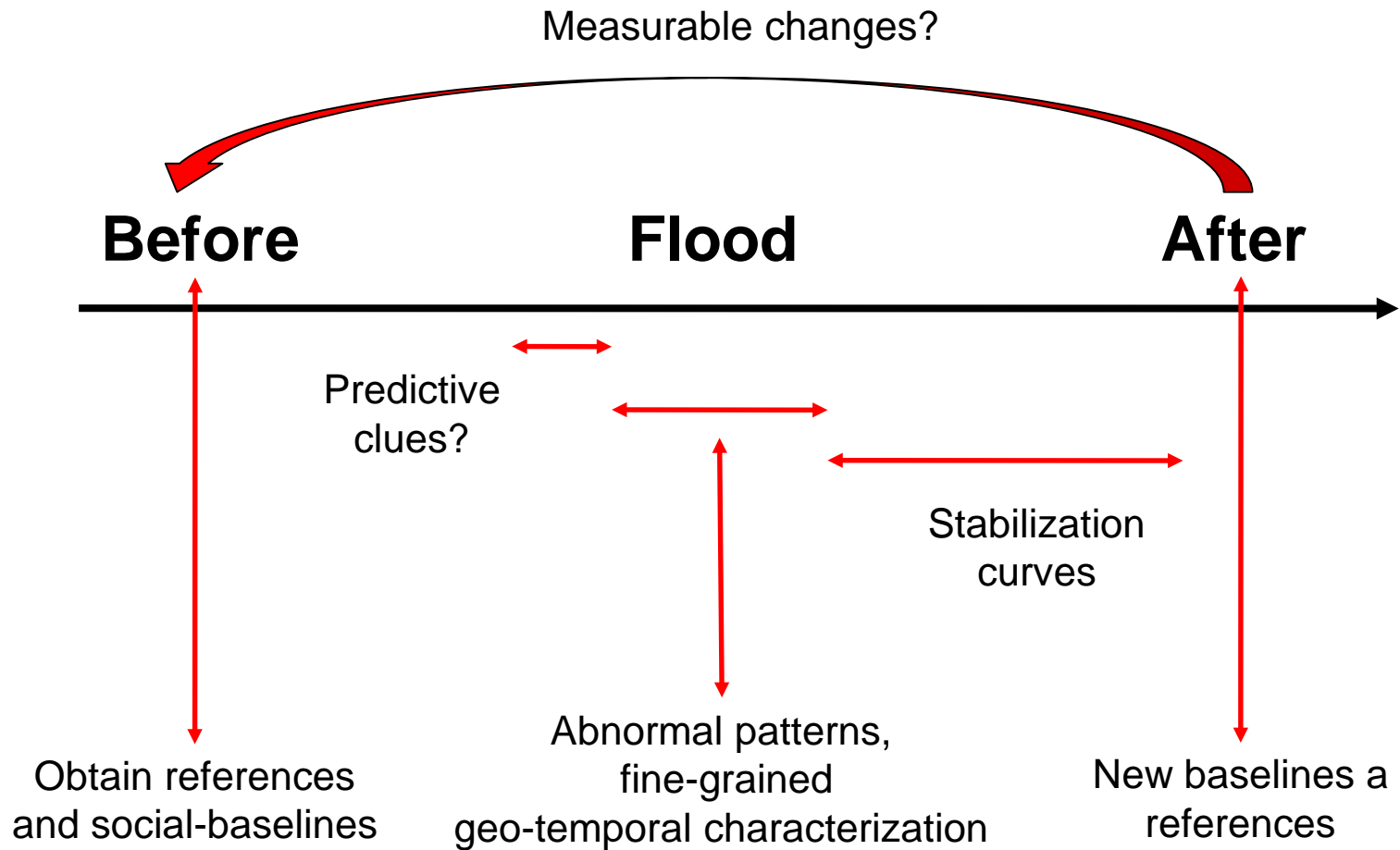


# Summary of Hypothesis

- Larger call volumes right after earthquake
- Shorter call durations ("check call")
- Longer calls at the end of the day
- Highly connected users contact larger number of peers
- Larger mobility patterns during earthquake



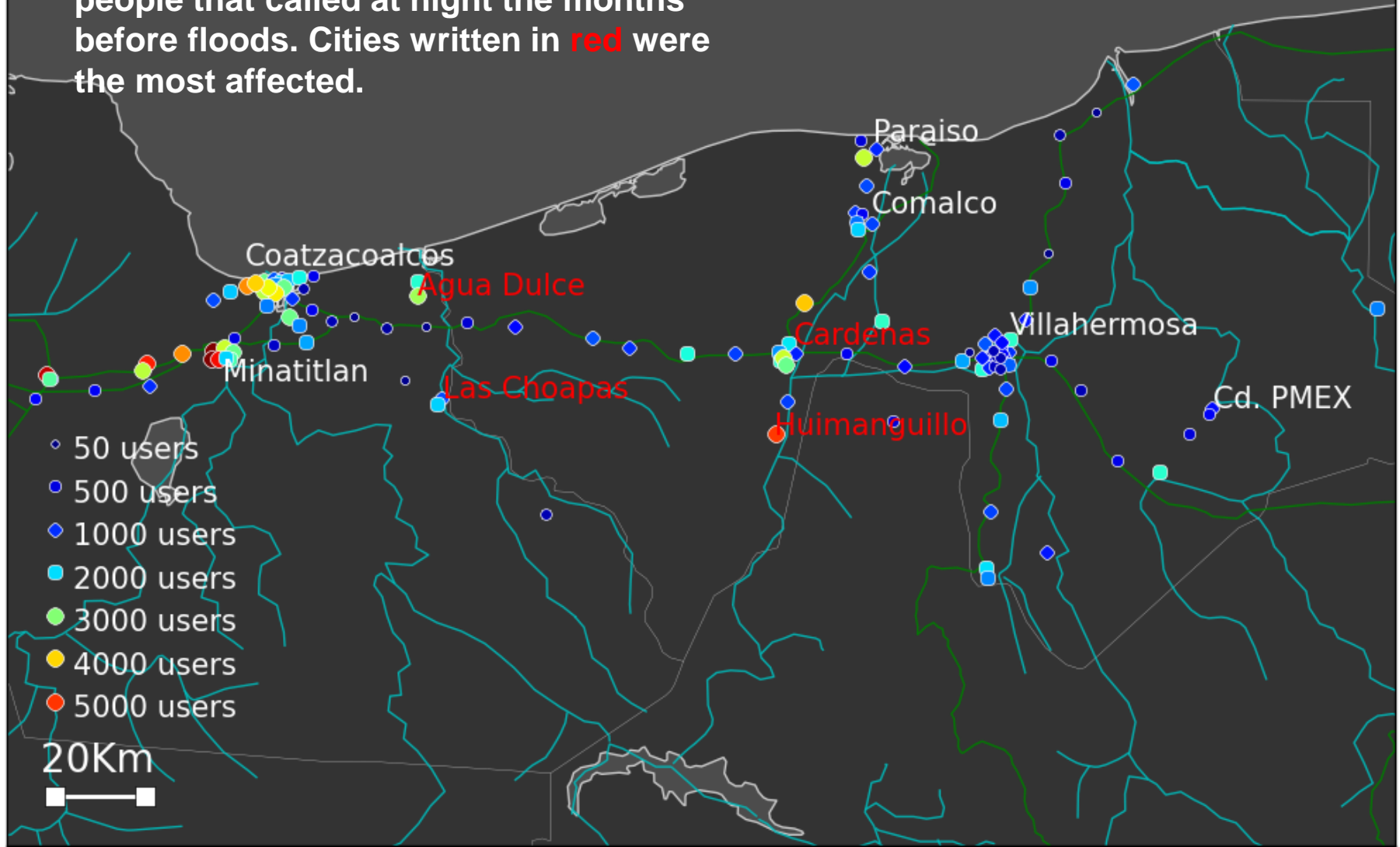
# Data analysis to study temporal evolution of natural disasters (Tabasco Floods)



# Who lives where

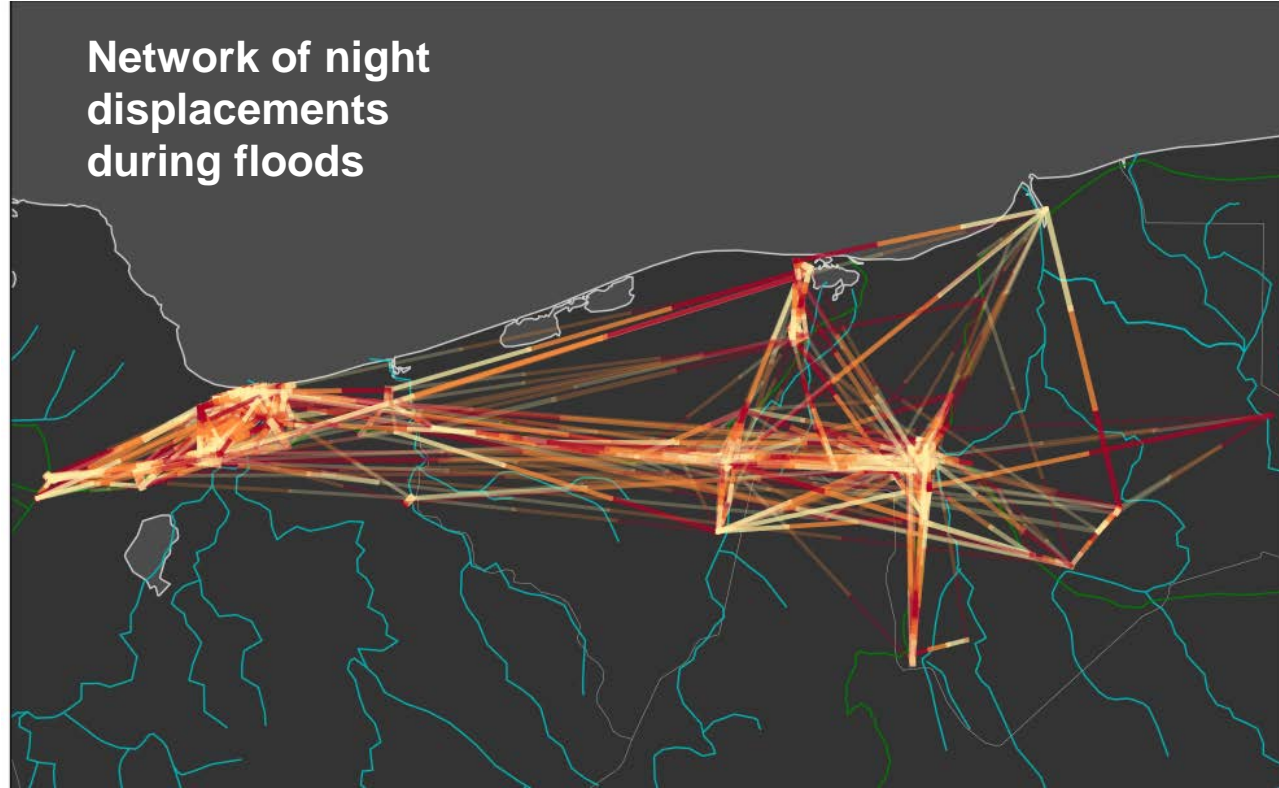
Size proportional to number of users served after 20hrs

This is how the map looks like when we consider the residence of the observed people that called at night the months before floods. Cities written in **red** were the most affected.



# Who changed residence

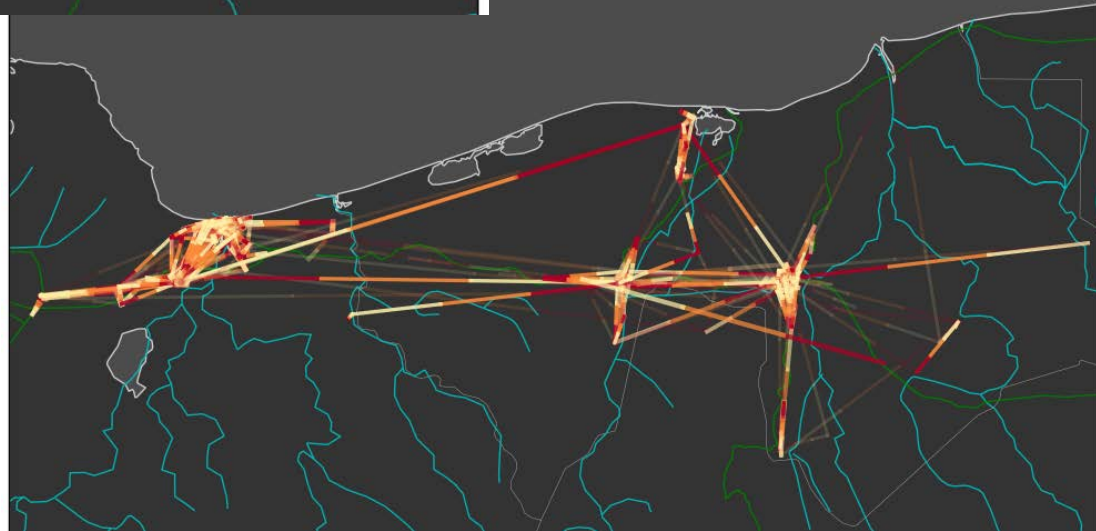
Network of night displacements during floods



Here we present a snapshot of the night displacements during floods and the same days one month before. The edge goes from red to pale yellow.

We see that the resulting network is much denser and presents more edges than the previous period.

Random period

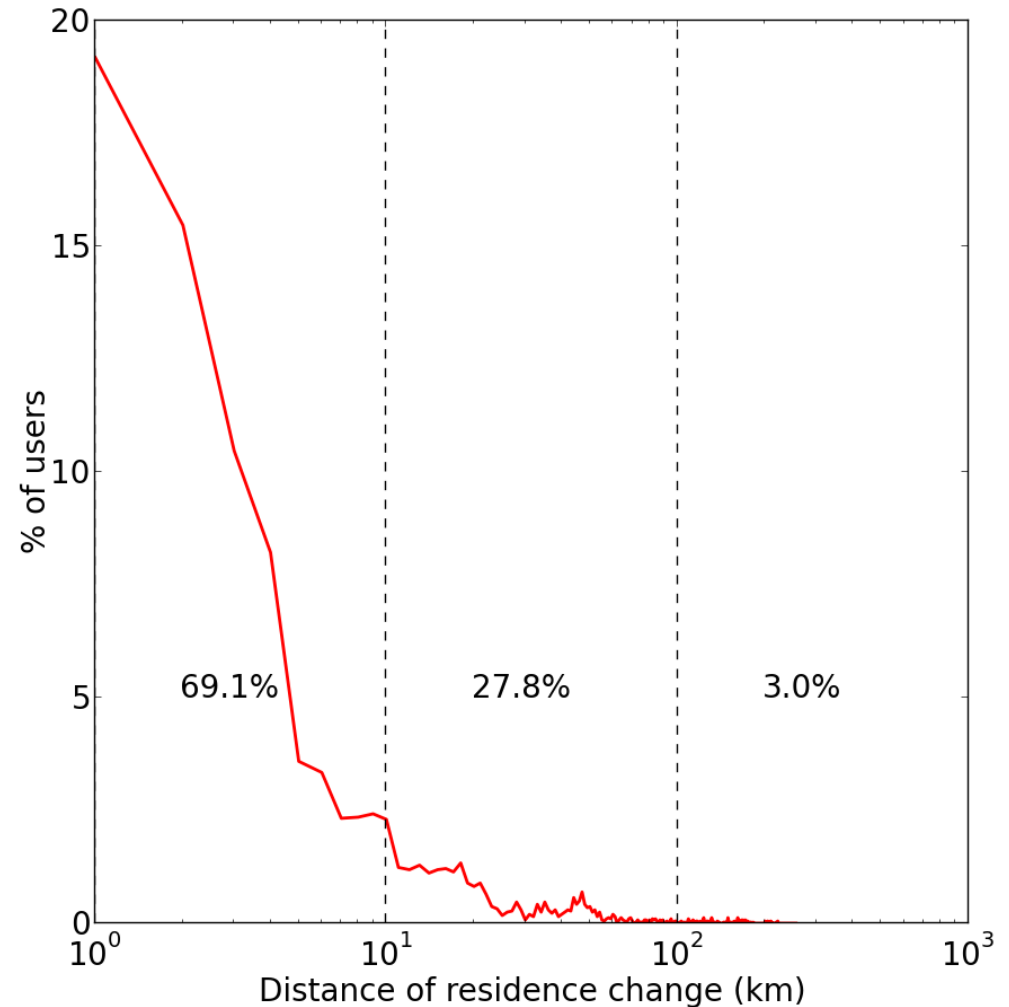


**Evacuation centers???**

# Who changed residence

In this figure we see the distribution of the distances between the old home and the “new” night location.

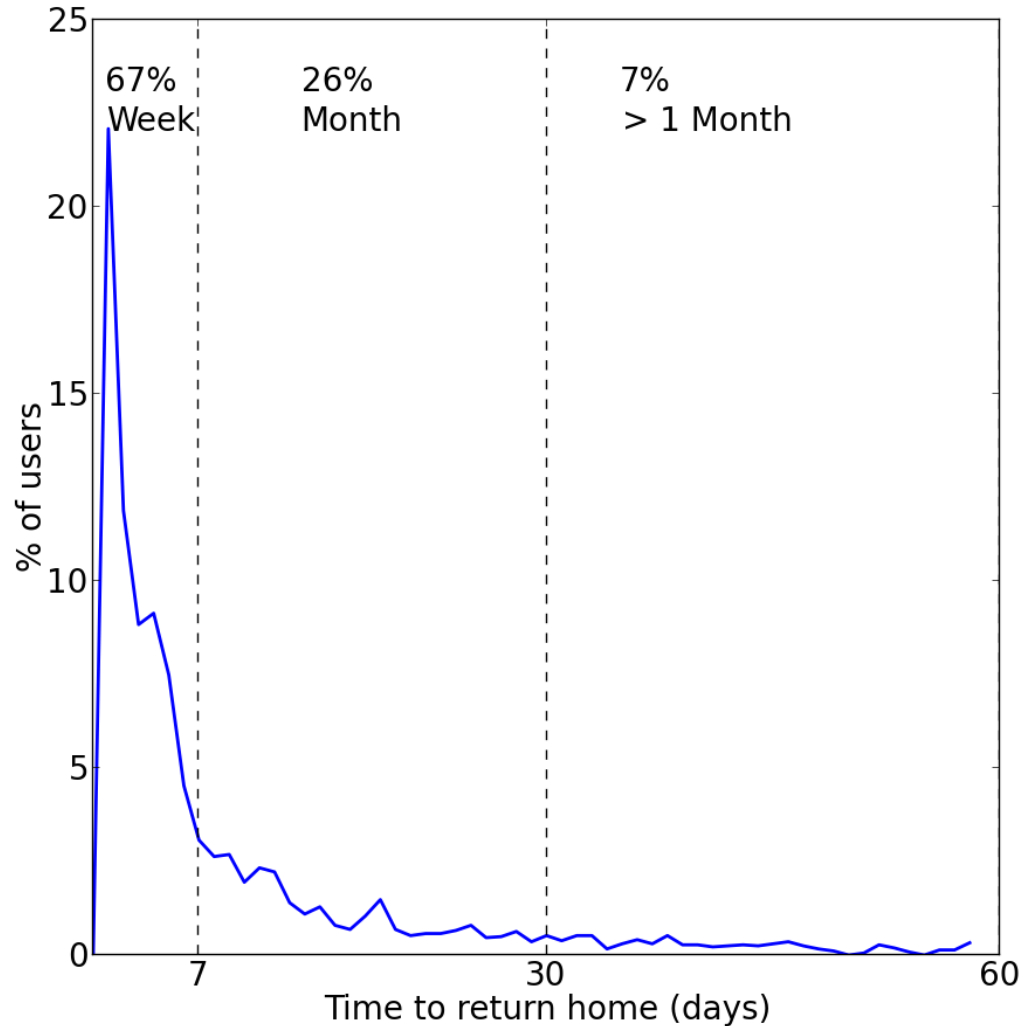
We see that 30% of users displaced more than 10kms and less than 3% of them displaced more than 100kms.



# Who returned home

In this figure we see the distribution of the time that took for displaced people to go back home.

We see that more than 60% of users returned in a time lapse of a week, while for 26% of users to between a week and a month to return, more than 8% took more than one month.





# Challenges



Ebola and big data

# Waiting on hold

Mobile-phone records would help combat the Ebola epidemic. But getting to look at them has proved hard

Oct 25th 2014 | From the print edition



Comment (5)

Timekeeper reading list

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40% of your peers are successfully addressing regulatory requirements

ups Get the Survey



Rex Features

IN THE battle against Ebola, mobile phones could be invaluable—not just in themselves, as devices that can be used to send people public-health information or let them call helpines, but also because of the data they generate. Phone companies use call-data records, or CDRs, to manage their networks and bill their customers. These records

Recent Activity

**Peer-to-peer rental**  
145 people recommend this.

**Why does liberal Iceland want to ban online pornography?**  
1,380 people recommend this.

**Is The Economist left- or right-wing?**  
2,533 people recommend this.

**Farming as rocket science**

## Regulatory and Social

1. Lack of updated regulation
2. Lack of clear guidelines regarding safe data handling, processing and sharing for humanitarian purposes
3. Risk of potential unintended consequences
4. Risk of creating a digital divide, unbalanced access to data and-or expertise on how to analyze it and make sense of it

## Technical

1. Representativeness of the data, generalization
2. Combination of data from multiple sources
3. Real-time analysis and prediction
4. Lack of ground truth → intervention to validate
5. Significant vs substantially significant
6. Correlations vs causality

## Privacy and Security

1. Potential privacy risks need to be minimized and understood. Control and transparency
2. Security and traceability of the data
3. Clear code of conduct and ethical principles
4. Strict access control when appropriate



# GRACIAS

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telefonica.com